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Gisslén et al.

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(54) ADVERSARIAL REINFORCEMENT LEARNING FOR PROCEDURAL CONTENT GENERATION AND IMPROVED GENERALIZATION

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(51) **Int. Cl.**
A63F 13/67 (2014.01)
A63F 13/56 (2014.01)
(Continued)

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CPC ***A63F 13/67*** (2014.09); ***A63F 13/56*** (2014.09); ***G06N 3/045*** (2023.01); ***G06N 3/08*** (2013.01)

(58) **Field of Classification Search**
CPC A63F 13/67; A63F 13/56; A63F 13/57; A63F 13/577; A63F 13/58; G06N 3/044; G06N 3/045; G06N 3/047
See application file for complete search history.

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(57) **ABSTRACT**

Methods, apparatus and systems are provided for training a first reinforcement-learning (RL) agent and a second RL agent coupled to a computer game environment using RL techniques. The first RL agent iteratively generates a sub-goal sequence in relation to an overall goal within the computer game environment, where the first RL agent generates a new sub-goal for the sub-goal sequence after a second RL agent, interacting with the computer game environment, successfully achieves a current sub-goal in the sub-goal sequence. The second RL agent iteratively interacts with the computer game environment to achieve the current sub-goal in which each iterative interaction includes an attempt by the second RL agent for interacting with the computer game environment to achieve the current sub-goal. The first RL agent is updated using a first reward issued when the second RL agent successfully achieves the current sub-goal. The second RL agent is updated when a second reward is issued by the computer game environment based on the performance of the second RL agent attempting to achieve said current sub-goal. Once validly trained, the first RL agent forms a final first RL agent for automatic procedural content generation (PCG) in the computer game envi-
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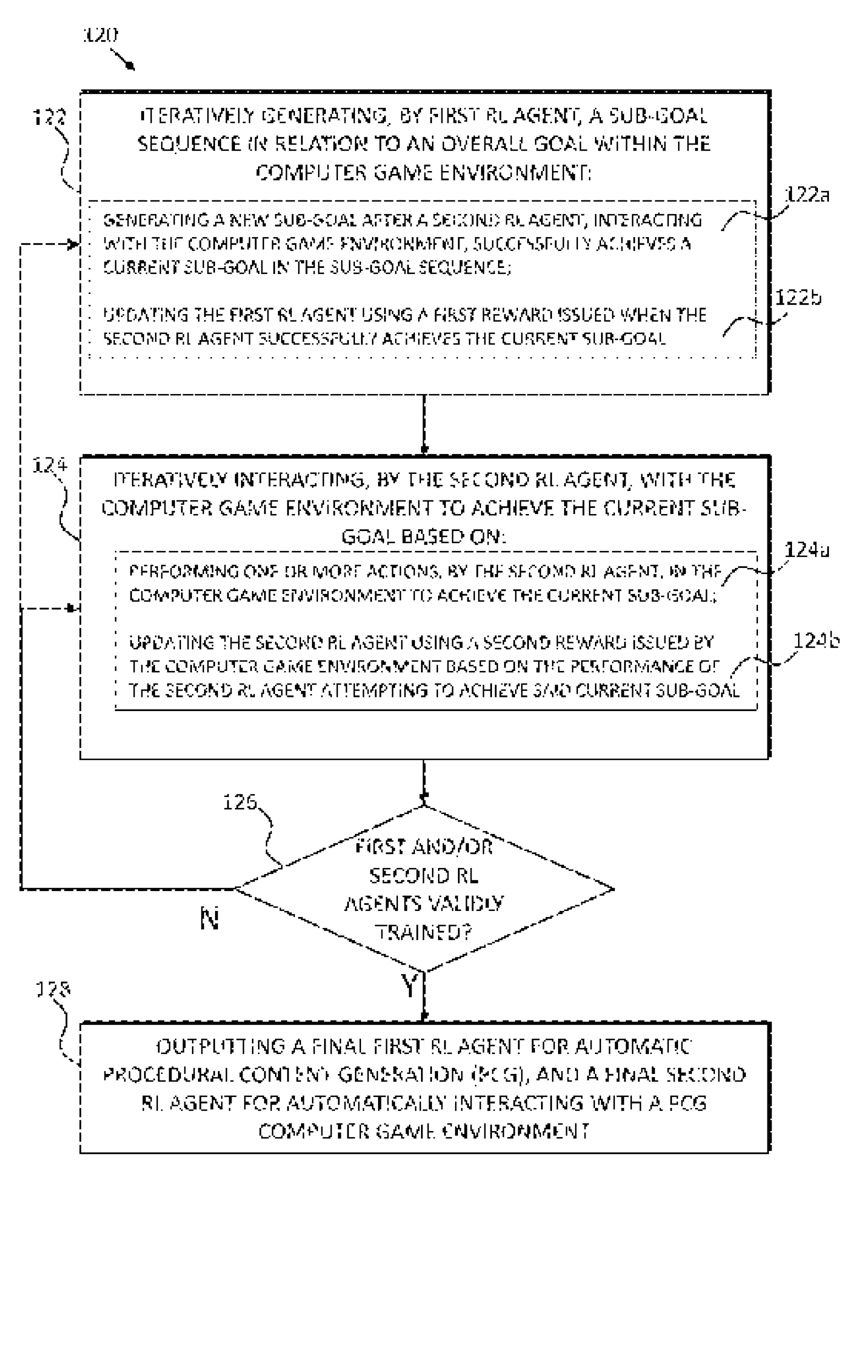

ronment and the second RL agent forms a final second RL agent for automatically interacting with a PCG computer game environment.

20 Claims, 14 Drawing Sheets

(51) **Int. Cl.**

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G06N 3/08	(2023.01)
G06N 3/045	(2023.01)

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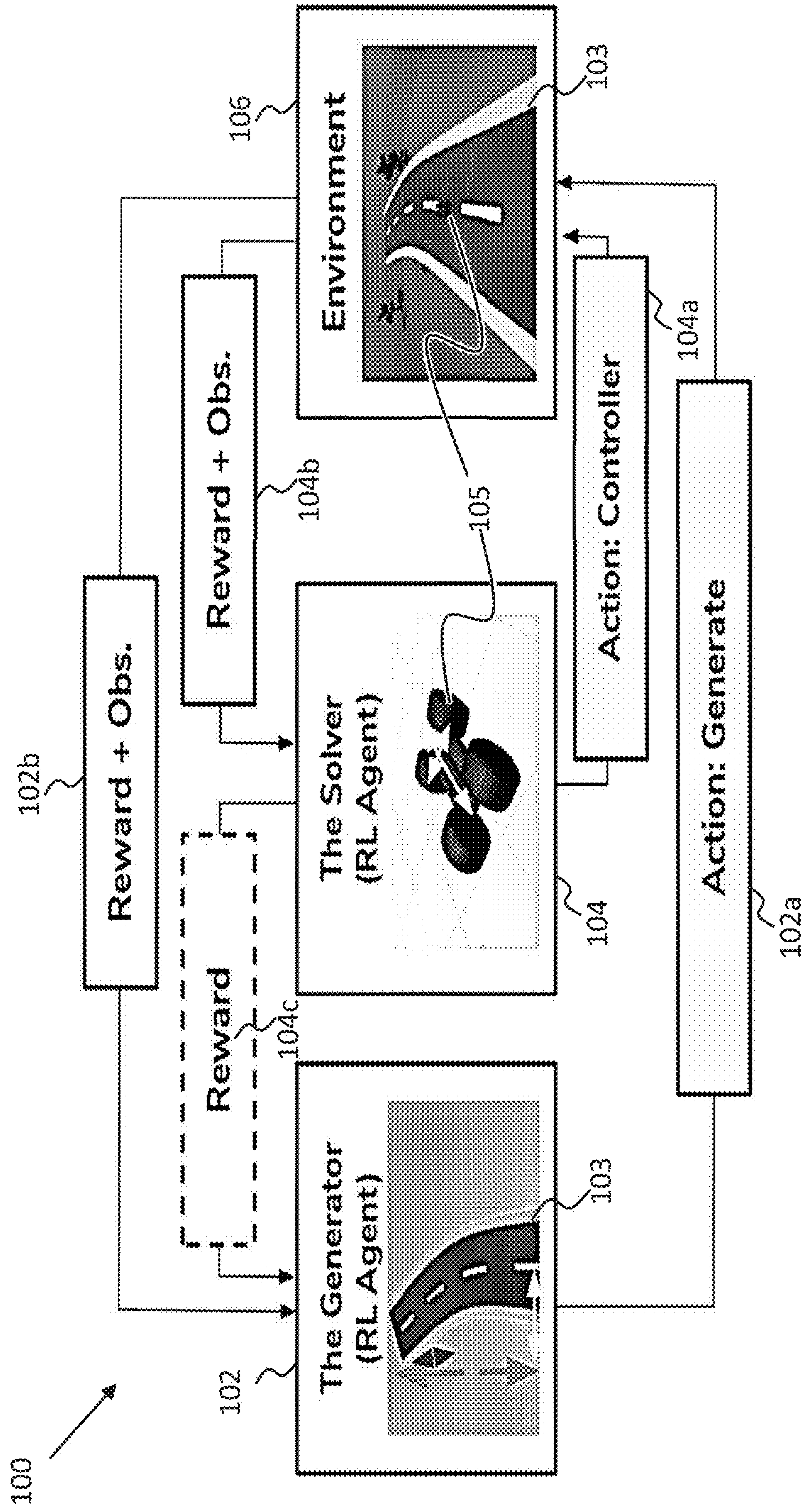
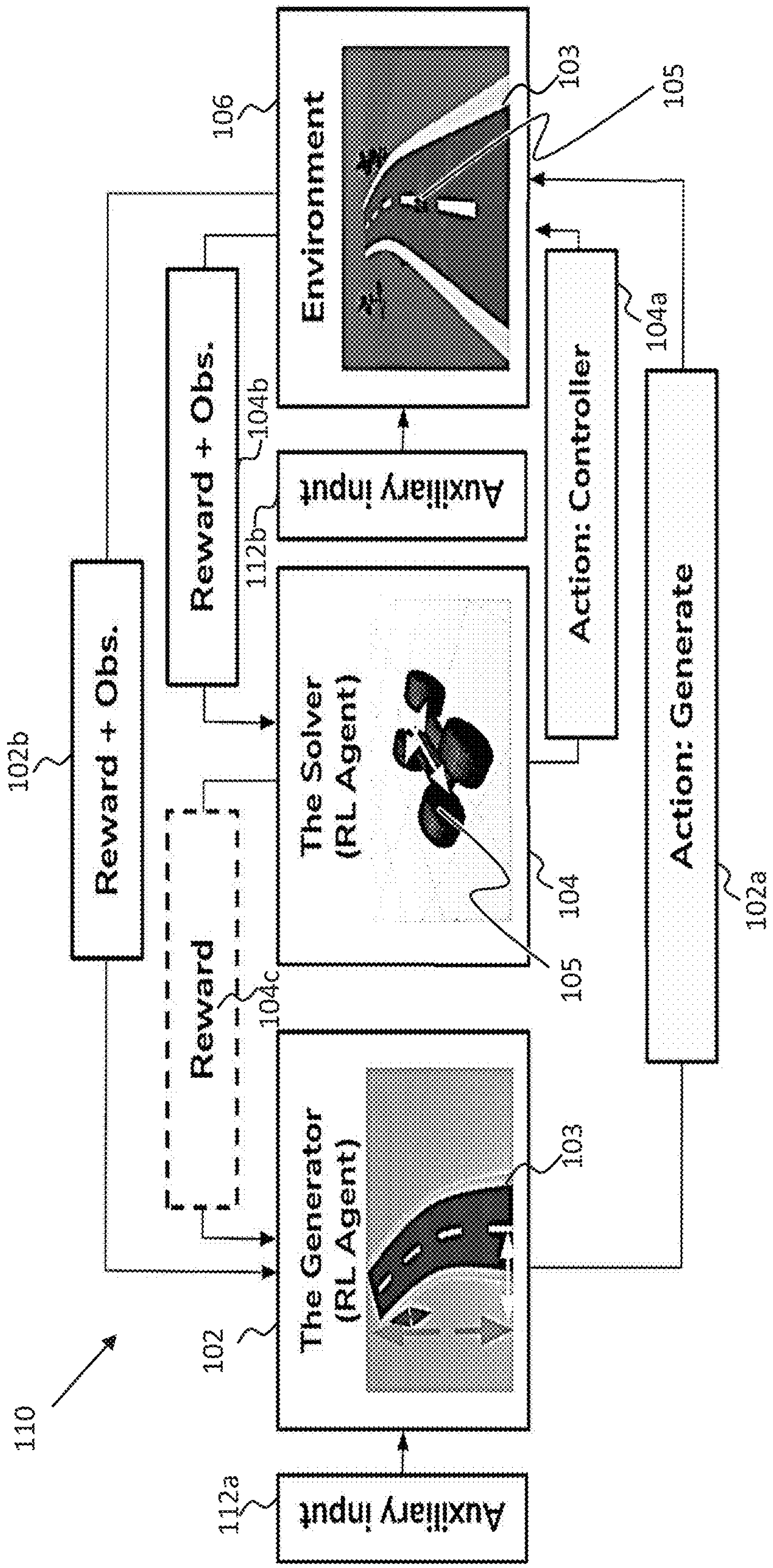

100
102
The Generator (RL Agent)
103
Reward
104c
Reward + Obs.
102b
The Solver (RL Agent)
104
105
Reward + Obs.
104b
Environment
106
103
Action: Controller
104a
Action: Generate
102a

FIG. 1a



110
112a
Auxiliary input
102
The Generator (RL Agent)
103
Reward
104c
Reward + Obs.
102b
Action: Generate
102a
The Solver (RL Agent)
104
105
112b
Auxiliary input
Reward + Obs.
104b
Action: Controller
104a
Environment
106
103
105

FIG. 1b

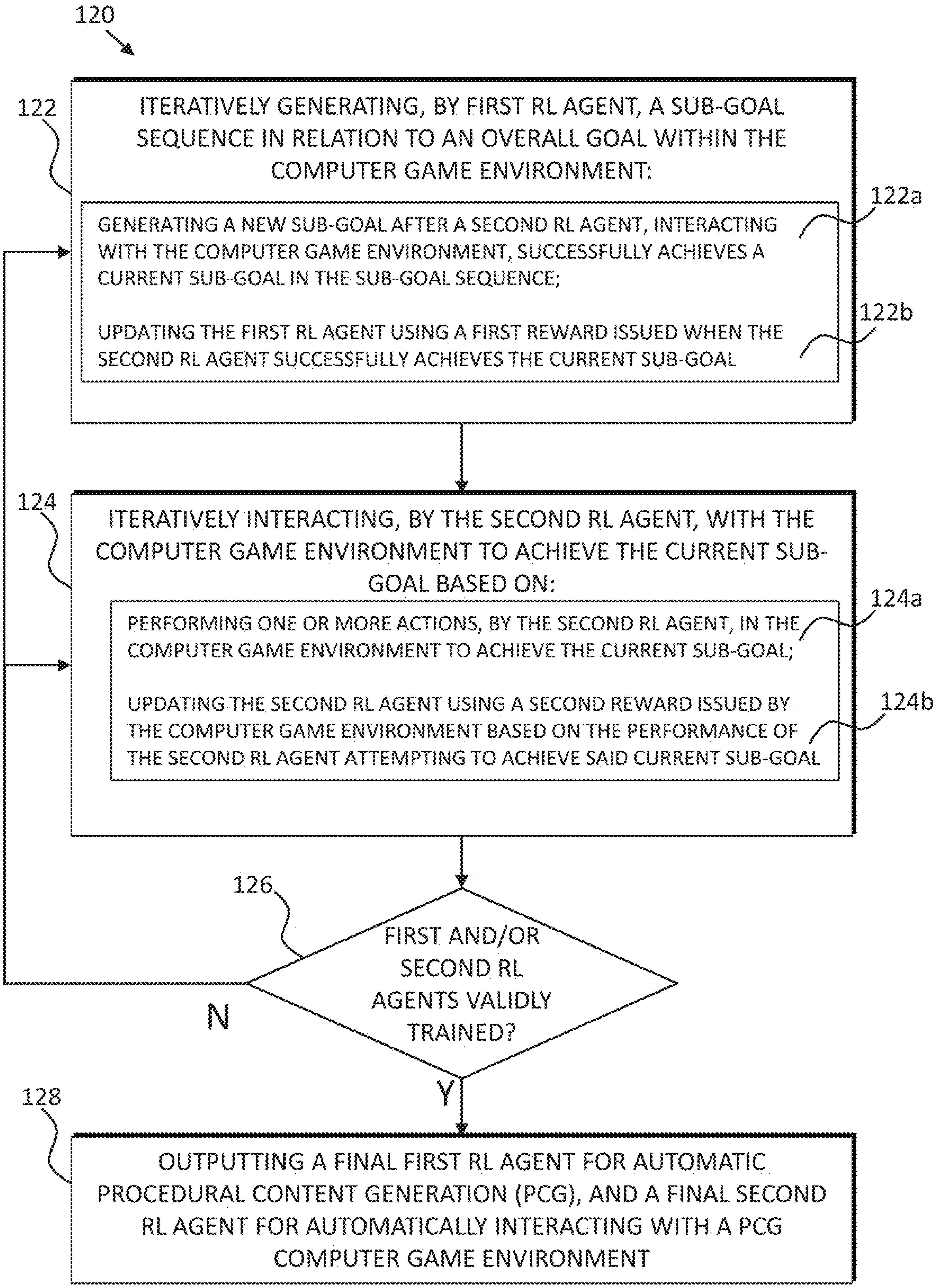

120
122
ITERATIVELY GENERATING, BY FIRST RL AGENT, A SUB-GOAL SEQUENCE IN RELATION TO AN OVERALL GOAL WITHIN THE COMPUTER GAME ENVIRONMENT:
122a
GENERATING A NEW SUB-GOAL AFTER A SECOND RL AGENT, INTERACTING WITH THE COMPUTER GAME ENVIRONMENT, SUCCESSFULLY ACHIEVES A CURRENT SUB-GOAL IN THE SUB-GOAL SEQUENCE;
122b
UPDATING THE FIRST RL AGENT USING A FIRST REWARD ISSUED WHEN THE SECOND RL AGENT SUCCESSFULLY ACHIEVES THE CURRENT SUB-GOAL
124
ITERATIVELY INTERACTING, BY THE SECOND RL AGENT, WITH THE COMPUTER GAME ENVIRONMENT TO ACHIEVE THE CURRENT SUB-GOAL BASED ON:
124a
PERFORMING ONE OR MORE ACTIONS, BY THE SECOND RL AGENT, IN THE COMPUTER GAME ENVIRONMENT TO ACHIEVE THE CURRENT SUB-GOAL;
124b
UPDATING THE SECOND RL AGENT USING A SECOND REWARD ISSUED BY THE COMPUTER GAME ENVIRONMENT BASED ON THE PERFORMANCE OF THE SECOND RL AGENT ATTEMPTING TO ACHIEVE SAID CURRENT SUB-GOAL
126
FIRST AND/OR SECOND RL AGENTS VALIDLY TRAINED?
N
Y
128
OUTPUTTING A FINAL FIRST RL AGENT FOR AUTOMATIC PROCEDURAL CONTENT GENERATION (PCG), AND A FINAL SECOND RL AGENT FOR AUTOMATICALLY INTERACTING WITH A PCG COMPUTER GAME ENVIRONMENT

FIG. 1c

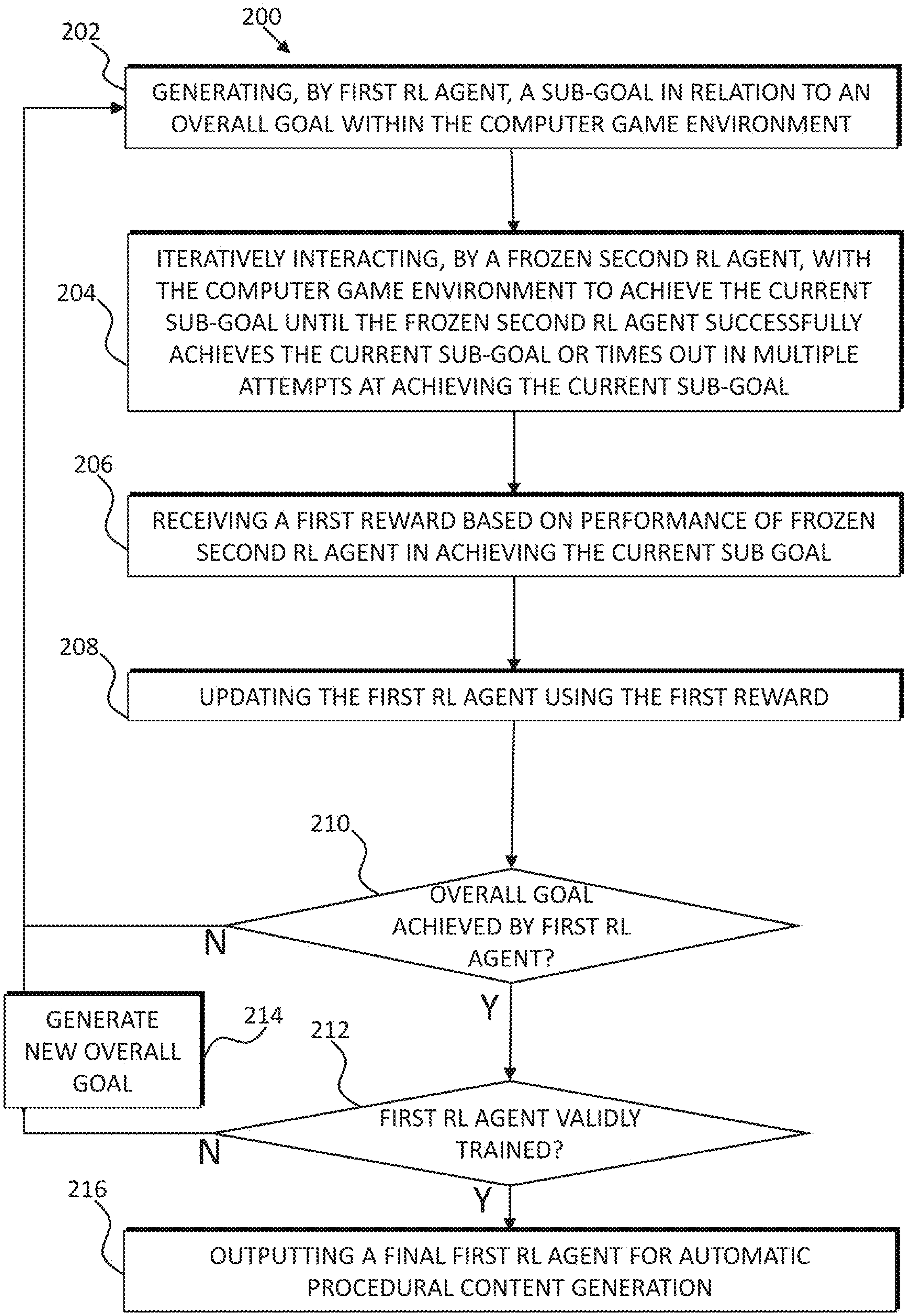
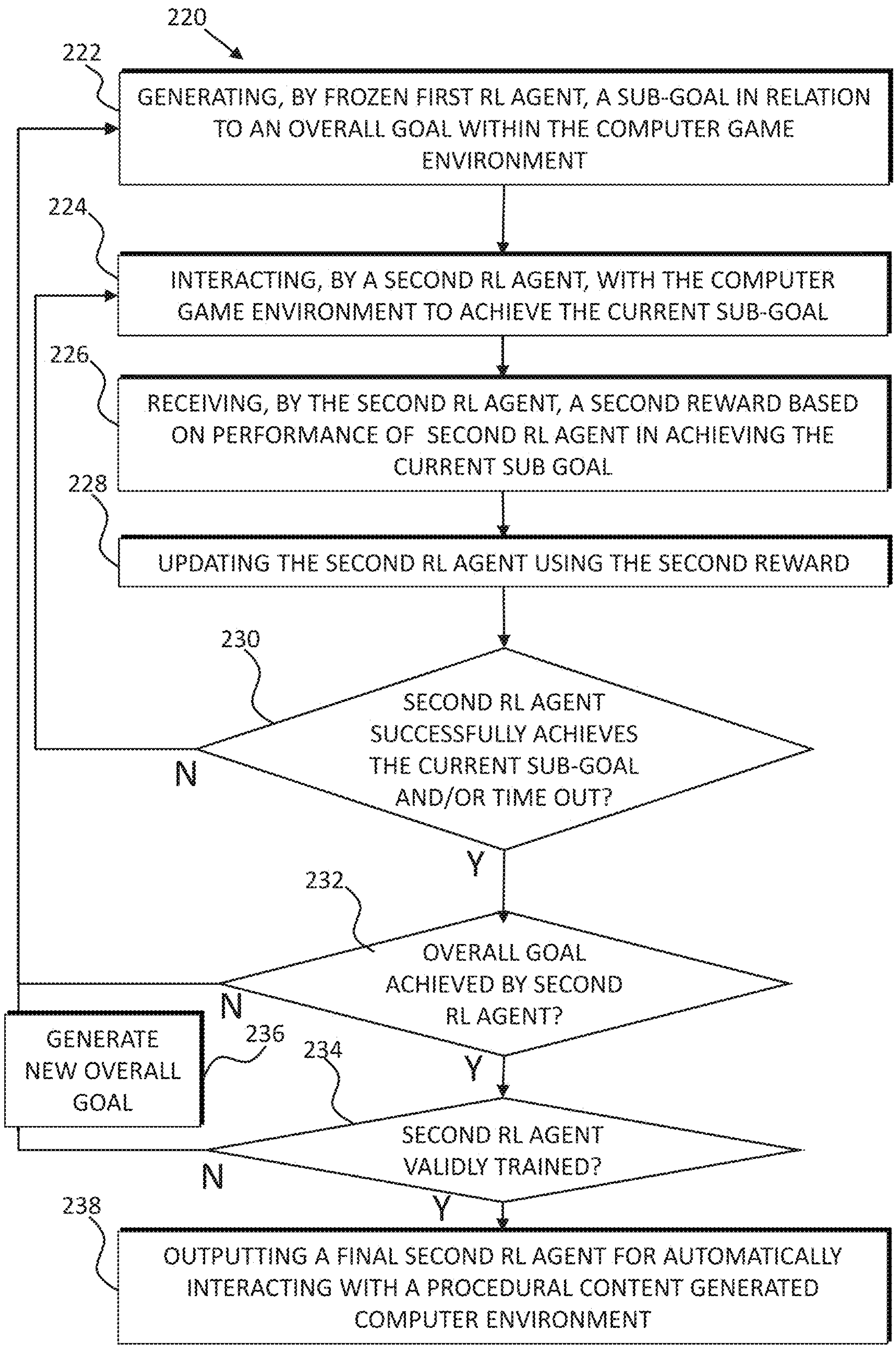

200
202
GENERATING, BY FIRST RL AGENT, A SUB-GOAL IN RELATION TO AN OVERALL GOAL WITHIN THE COMPUTER GAME ENVIRONMENT
204
ITERATIVELY INTERACTING, BY A FROZEN SECOND RL AGENT, WITH THE COMPUTER GAME ENVIRONMENT TO ACHIEVE THE CURRENT SUB-GOAL UNTIL THE FROZEN SECOND RL AGENT SUCCESSFULLY ACHIEVES THE CURRENT SUB-GOAL OR TIMES OUT IN MULTIPLE ATTEMPTS AT ACHIEVING THE CURRENT SUB-GOAL
206
RECEIVING A FIRST REWARD BASED ON PERFORMANCE OF FROZEN SECOND RL AGENT IN ACHIEVING THE CURRENT SUB GOAL
208
UPDATING THE FIRST RL AGENT USING THE FIRST REWARD
210
OVERALL GOAL ACHIEVED BY FIRST RL AGENT?
N
Y
GENERATE NEW OVERALL GOAL
214
212
FIRST RL AGENT VALIDLY TRAINED?
N
Y
216
OUTPUTTING A FINAL FIRST RL AGENT FOR AUTOMATIC PROCEDURAL CONTENT GENERATION

FIG. 2a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222
GENERATING, BY FROZEN FIRST RL AGENT, A SUB-GOAL IN RELATION TO AN OVERALL GOAL WITHIN THE COMPUTER GAME ENVIRONMENT
224
INTERACTING, BY A SECOND RL AGENT, WITH THE COMPUTER GAME ENVIRONMENT TO ACHIEVE THE CURRENT SUB-GOAL
226
RECEIVING, BY THE SECOND RL AGENT, A SECOND REWARD BASED ON PERFORMANCE OF SECOND RL AGENT IN ACHIEVING THE CURRENT SUB GOAL
228
UPDATING THE SECOND RL AGENT USING THE SECOND REWARD
230
SECOND RL AGENT SUCCESSFULLY ACHIEVES THE CURRENT SUB-GOAL AND/OR TIME OUT?
N
Y
232
OVERALL GOAL ACHIEVED BY SECOND RL AGENT?
N
Y
GENERATE NEW OVERALL GOAL
236
234
SECOND RL AGENT VALIDLY TRAINED?
N
Y
238
OUTPUTTING A FINAL SECOND RL AGENT FOR AUTOMATICALLY INTERACTING WITH A PROCEDURAL CONTENT GENERATED COMPUTER ENVIRONMENT

FIG. 2b

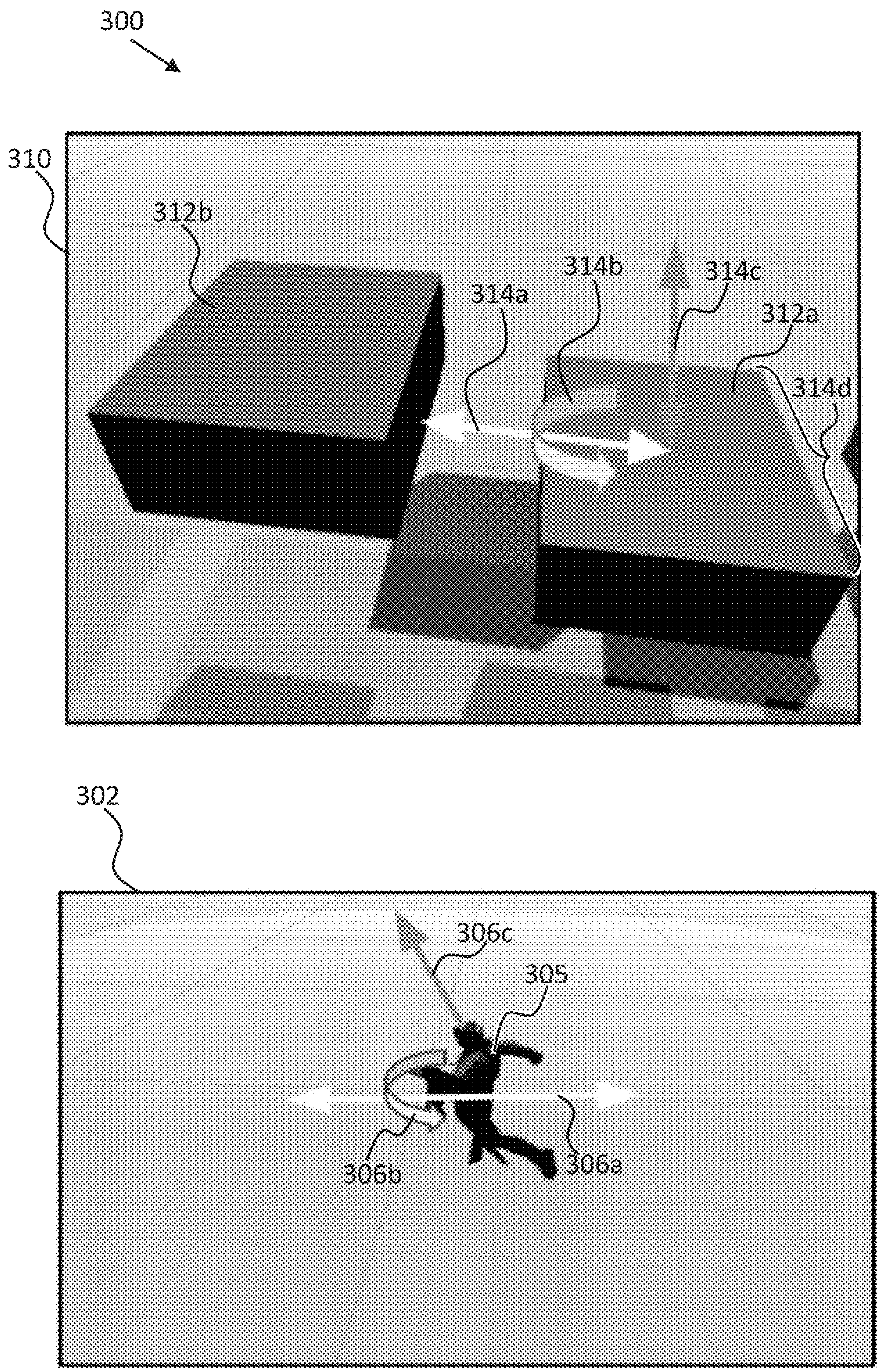

FIG. 3

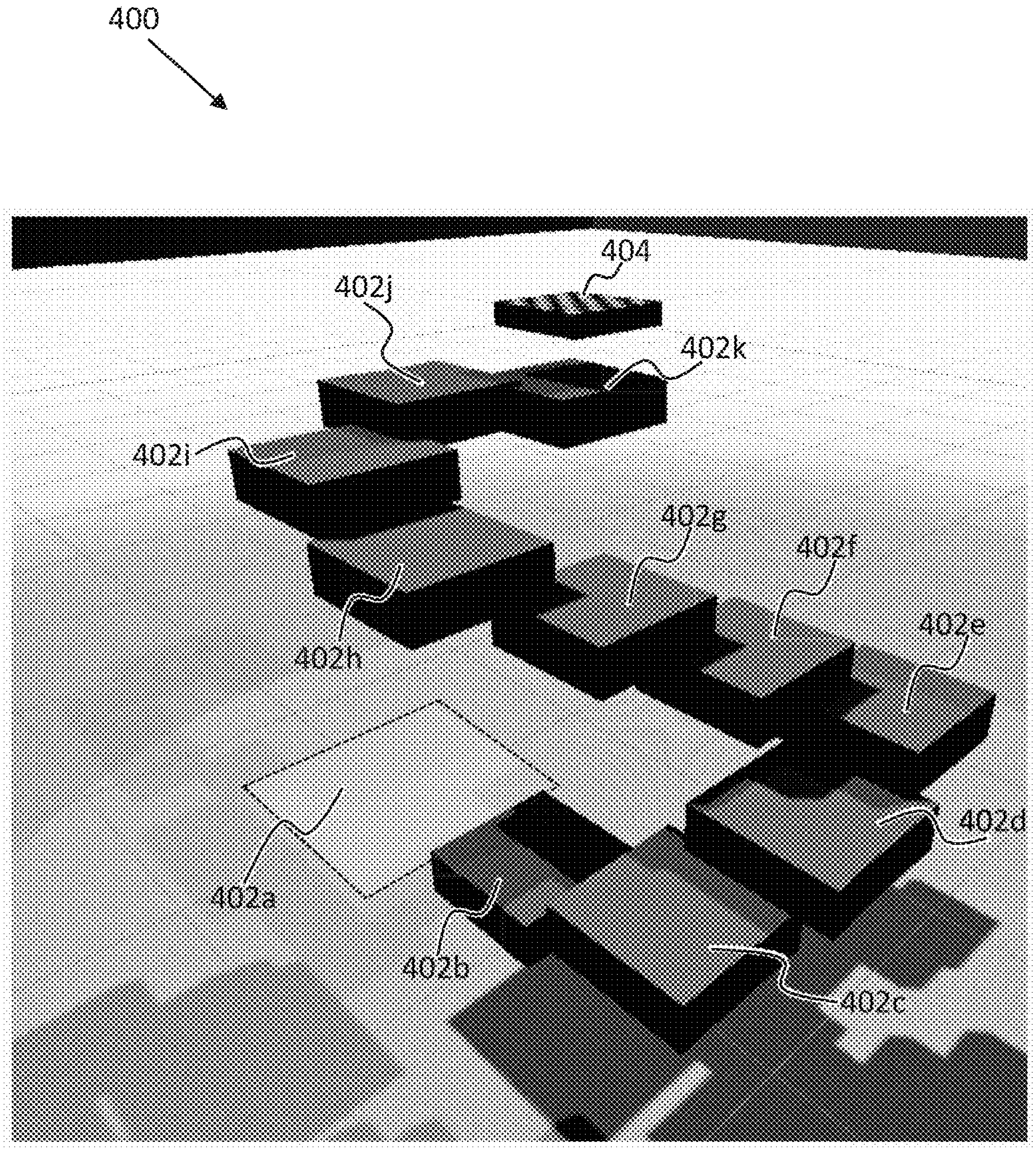
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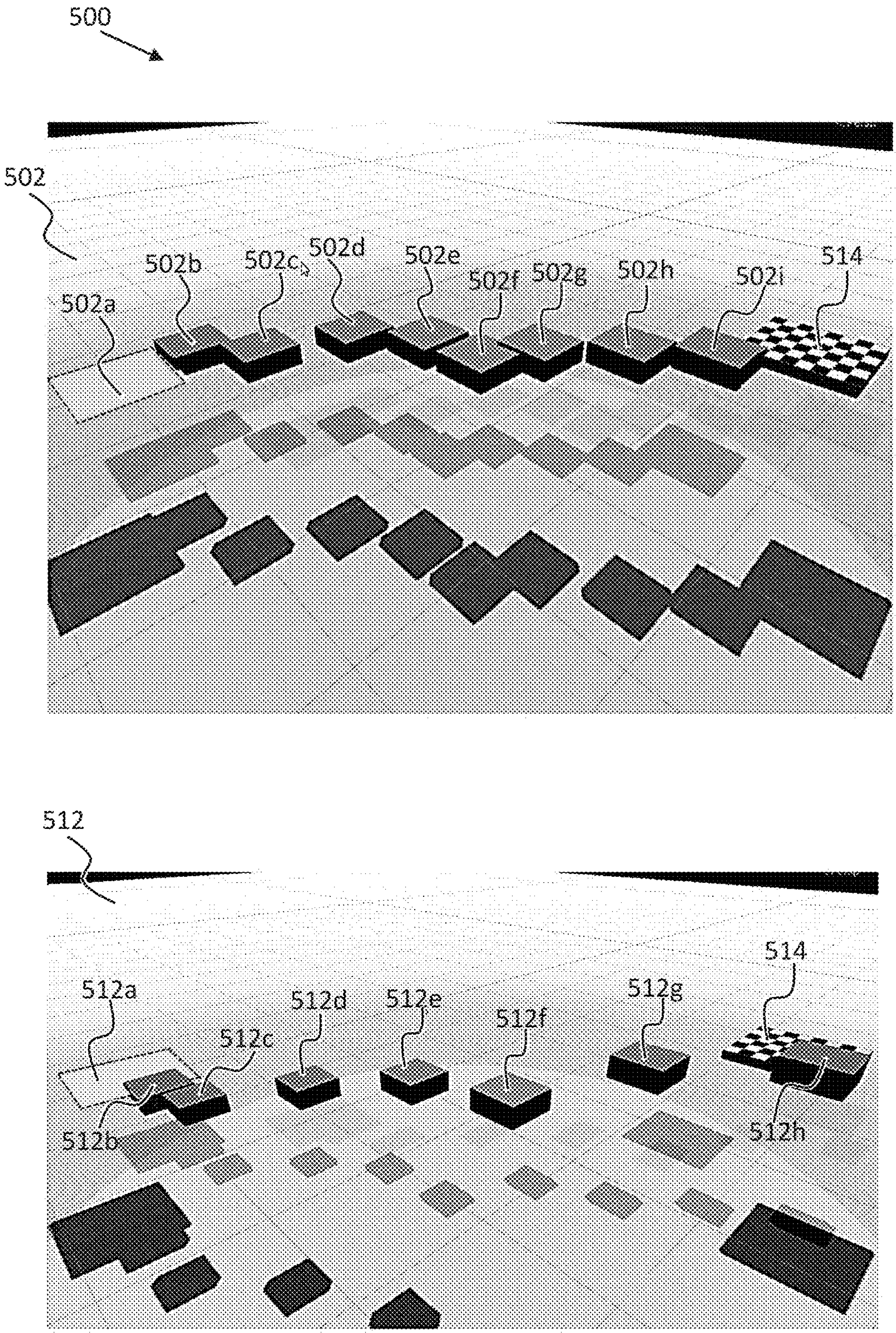
FIG. 4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512f
512g
512h
514

FIG. 5

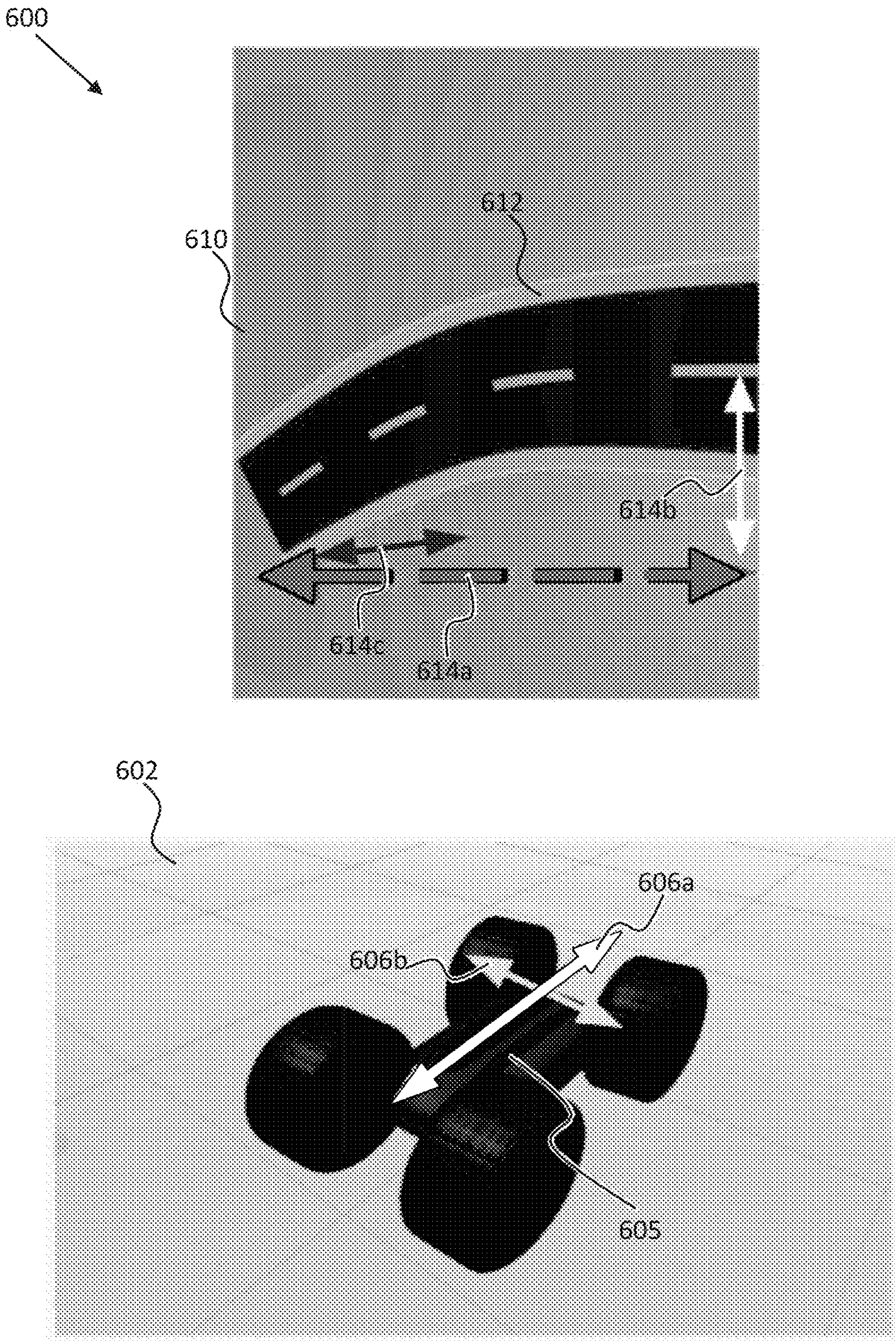
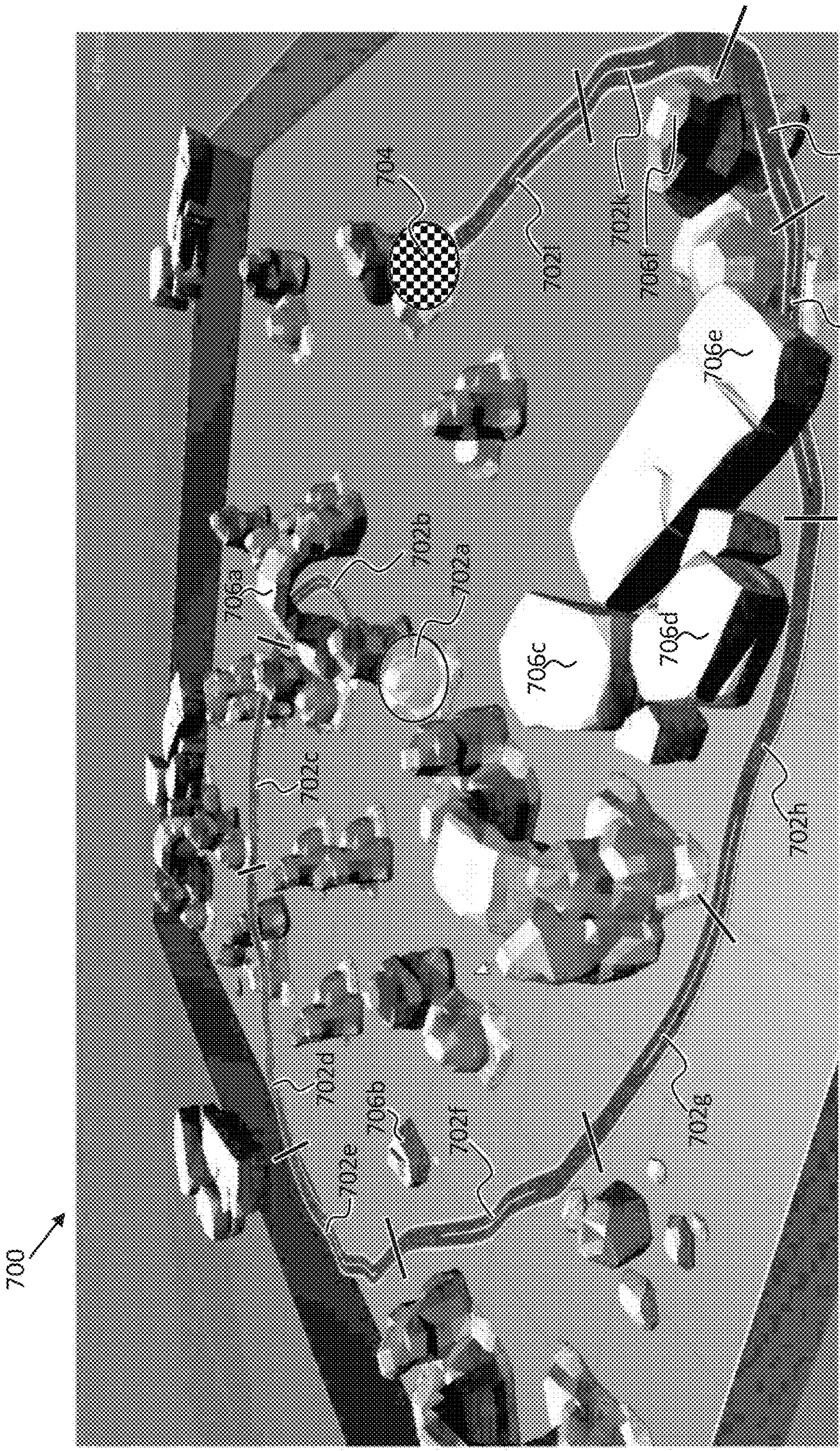


FIG. 6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702a
702b
702c
702d
702e
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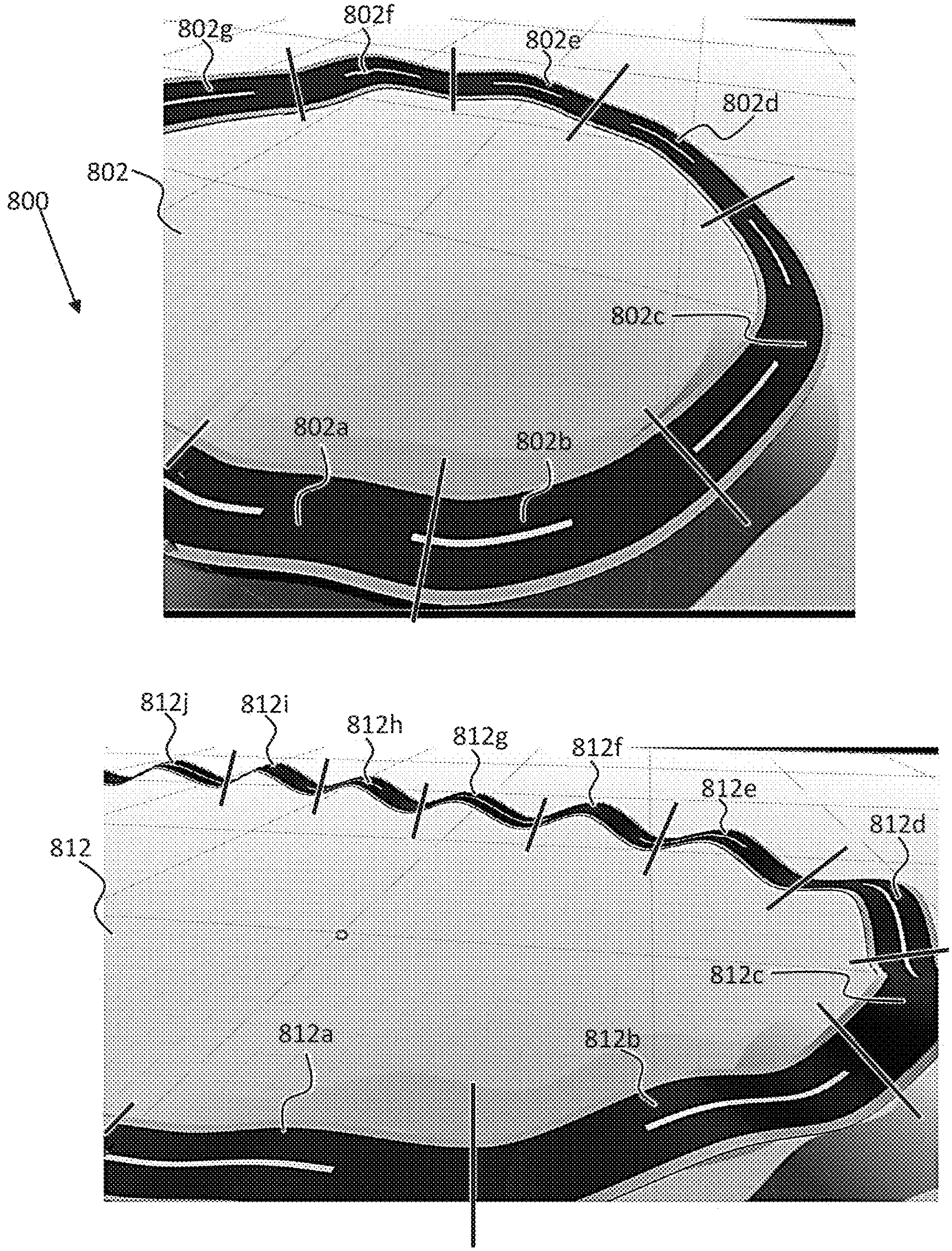
706e
706f

FIG. 7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802
802a
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802f
802g
812
812a
812b
812c
812d
812e
812f
812g
812h
812i
812j

FIG. 8

900

Aux. value	Fixed	Rule PCG	ARL PCG
1 (Easy)	0.301±0.154 (21.9±0.7 m/s)	0.987±0.154 (23.0±0.4)	1.000±0.000 (21.8±0.5 m/s)
0 (Moderate)	0.044±0.048 (19.0±0.7 m/s)	0.979±0.035 (20.6±1.1 m/s)	0.972±0.029 (19.6±0.5 m/s)
-0.5 (Hard)	0.013±0.037 (16.6±1.2 m/s)	0.804±0.303 (15.1±2.4 m/s)	0.781±0.172 (16.6±1.1 m/s)
-0.75	0.005±0.008 (15.6±1.03 m/s)	0.485±0.402 (13.9±2.0 m/s)	0.436±0.234 (15.4±1.0 m/s)
-1 (Hardest)	0.000±0.010 (14.7±0.7 m/s)	0.228±0.339 (12.6±1.8 m/s)	0.206±0.157 (14.9±0.6 m/s)

FIG. 9

1000

Aux. value	Fixed	Rule PCG	ARL PCG
1 (Easy)	0.0±0.0	0.776±0.154	0.824±0.185
0.5	0.0±0.0	0.692±0.350	0.741±0.285
0 (Moderate)	0.0±0.0	0.386±0.235	0.728±0.284
-0.5 (Hard)	0.0±0.0	0.148±0.165	0.360±0.276
-0.75	0.0±0.0	0.081±0.125	0.353±0.222
-1 (Hardest)	0.0±0.0	0.053±0.037	0.183±0.139

FIG. 10

1100

	Platform Game	*Racing Game*
Fixed track	0.081±0.205, 0.200 (54 steps)	0.022±0.021 (16.5 m/s)
Rule PCG	0.233±0.200, 0.950 (451 steps)	0.139±0.165 (17.1 m/s)
Fixed aux.	0.173±0.195, 0.900 (442 steps)	0.072±0.082 (15.7 m/s)
ARL PCG	0.457±0.211, 1.000 (467 steps)	0.271±0.137 (18.6 m/s)

FIG. 11

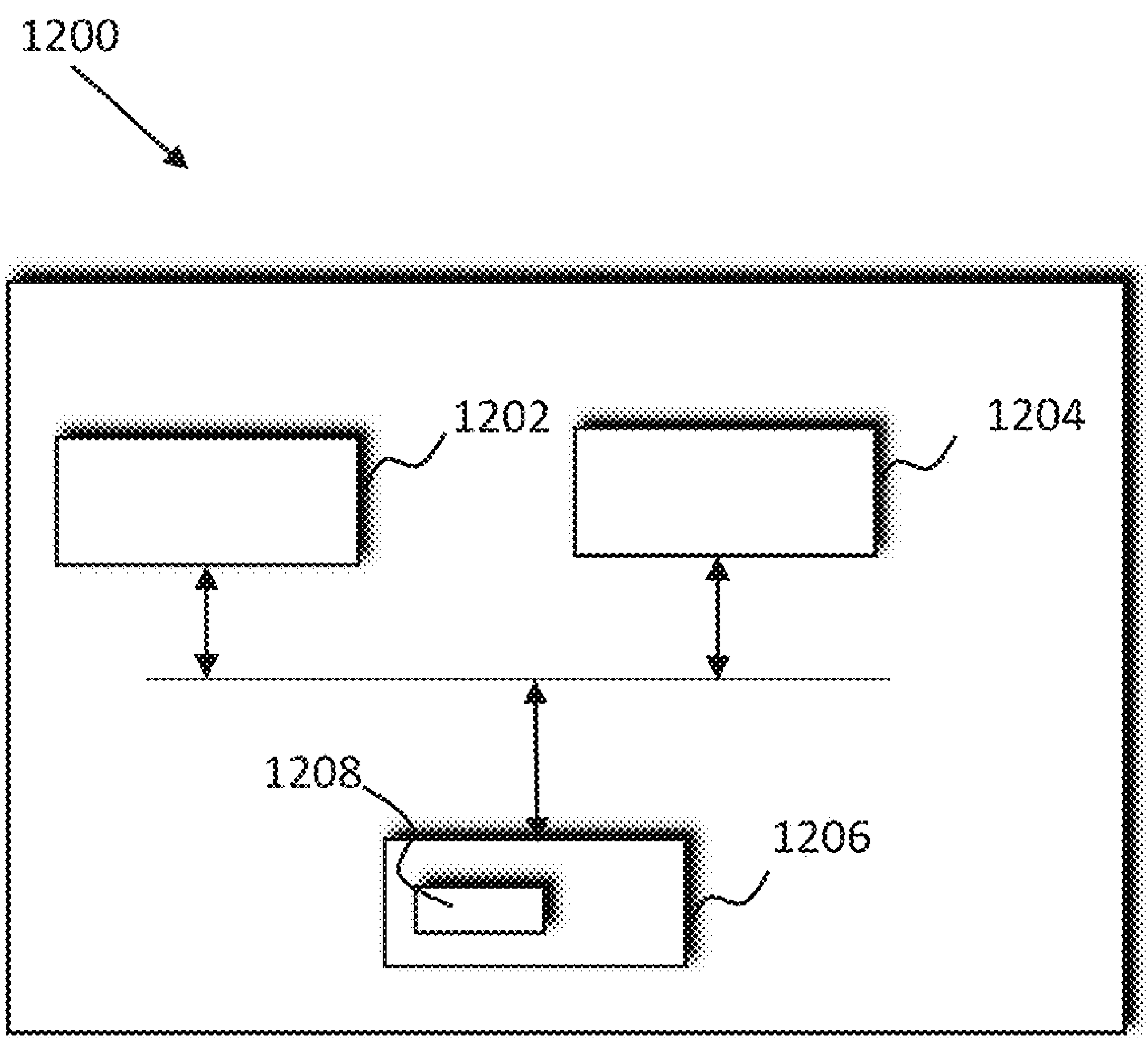

FIG. 12

ADVERSARIAL REINFORCEMENT LEARNING FOR PROCEDURAL CONTENT GENERATION AND IMPROVED GENERALIZATION

TECHNICAL FIELD

The present application relates to apparatus, systems and method(s) for using adversarial reinforcement-learning (RL) techniques to train a first RL agent to perform procedural content generation (PCG) for a computer game environment of a video game and train a second RL agent with improved generalization for interacting with a generated PCG computer game environment.

BACKGROUND

Training RL agents for interacting with unseen environments is a notoriously difficult task. This is particularly so for computer game environments of video games. Typically, trained RL player or solver agents are used to imitate a player character or a non-player character (e.g. an adversary to a player character) within the computer game environment of a video game. One popular approach is to procedurally generate different computer game environments in order to increase the generalisability of such trained RL agents. While existing RL approaches have been very successful at creating RL player agents that can solve problems in computer game environments and/or interacting with said computer game environments to achieve one or more goals with "super-human" performance, such RL player agents lack generalizability in part because their training and validation sets are often the same.

Typically, these RL agents are trained on such specific computer game environments that they become "overfitted". That is, there is a problem with these RL agents in that they have essentially "memorized" only those computer game environments on which they have been trained. They are then unable to generalize well or adapt to new or previously unseen computer game environments. The difficulty in training RL agents that are generalizable is due, in part, to the designer of a video game being unable to create enough diverse training datasets, i.e. different computer game environments. Although scripting may assist a designer in creating different procedural content generated (PCG) computer game environments, but the resulting training datasets are still very limited and resulting RL agents still overfitted.

This makes RL agents trained based on such training datasets less useful in game development and/or during game play, where the computer game environment including the assets, non-player characters, and/or other player characters and the like etc. may change or adapt on a day-to-day basis or in real-time. For example, in the computer game environment said assets, NPCs and/or other player characters and the like may also include artificial intelligence aspects resulting in different and unknown future behaviours. Most computer game environments are now continually changing or adapting. Trained RL agents that are overfitted are typically unable to cope due to the adapting computer game environment. Such trained RL agents also are less useful for handling automated in-game content-creation and/or testing.

There is a desire for a methodology, apparatus, systems and/or an architecture capable of generating a multitude of diverse PCG computer game environments whilst at the same time training RL player/solver agents on ever-changing computer game environments whilst ensuring such trained RL player/solver agents are more generalizable, adaptable and useful in unseen scenarios and/or computer game environments.

The embodiments described below are not limited to implementations which solve any or all of the disadvantages of the known approaches described above.

SUMMARY

This Summary is provided to introduce a selection of concepts in a simplified form that are further described below in the Detailed Description. This Summary is not intended to identify key features or essential features of the claimed subject matter, nor is it intended to be used to determine the scope of the claimed subject matter; variants and alternative features which facilitate the working of the invention and/or serve to achieve a substantially similar technical effect should be considered as falling into the scope of the invention disclosed herein.

The present disclosure provides method(s), apparatus and system(s) for performing procedural content generation (PCG) for computer game environments and automatically interacting with said PCG computer game environments using adversarial deep reinforcement-learning (RL) techniques for training a first RL agent (a so-called Generator) for generating a PCG computer game environment, and training at least one second RL agent (a so-called Solver) for interacting with the PCG computer game environment and solving/traversing sub-goals and/or overall goals within said PCG computer game environment. During training, the Generator receives a first reward signal based on the performance of the Solver which encourages the computer game environment design to be challenging but not impossible, whilst the Solver receives a second reward signal based on its performance interacting in the computer game environment designed and generated by the Generator. This provides the advantages of the Solver achieving better generalization through the generated challenges from the Generator, whilst the Generator is able to better create diverse PCG computer game environments that are playable/solvable by the Solver. The resulting trained first RL agent is configured for generating PCG computer game environments and the resulting trained second RL agent is configured to interacting PCG computer game environments for assisting game designers in robustly testing PCG computer game environments.

As an option, to further drive diversity, generalisability and control of the computer game environment generation by the Generator and/or interaction by the Solver, one or more auxiliary diversity input signals may be applied to the reward function of the Generator and/or computer game environment, which causes the Generator to generate previously unseen computer game environments using the auxiliary diversity input signal as a control variable by a game designer. This may provide the further advantages of the Solver achieving enhanced generalization through the generated challenges from the Generator based on the value of the auxiliary diversity input signal, whilst the Generator is further enhanced in creating PCG computer game environments with even more diversity that are playable/solvable by the enhanced Solver.

According to a first aspect of this specification, there is disclosed a computer-implemented method for training a first reinforcement-learning (RL) agent and a second RL agent coupled to a computer game environment using RL techniques, the computer-implemented method comprising: iteratively generating, by the first RL agent, a sub-goal

sequence in relation to an overall goal within the computer game environment, based on: generating a new sub-goal for the sub-goal sequence after a second RL agent, interacting with the computer game environment, successfully achieves a current sub-goal in the sub-goal sequence; and updating the first RL agent using a first reward issued when the second RL agent successfully achieves the current sub-goal. The computer-implemented method further comprising: iteratively interacting, by the second RL agent, with the computer game environment to achieve the current sub-goal based on: performing one or more actions, by the second RL agent, in the computer game environment to achieve the current sub-goal; and updating the second RL agent using a second reward issued by the computer game environment based on the performance of the second RL agent attempting to achieve said current sub-goal. Once the first and second RL agents are validly trained, outputting a final first RL agent for automatic PCG in the computer game environment, and a final second RL agent for automatically interacting with a PCG computer game environment.

The method may further comprise applying the auxiliary diversity signal to the reward function of the first RL agent, the reward function of the first RL agent comprising a combination of an external reward and an internal reward, the external reward based on the first reward and the internal reward based on the auxiliary diversity signal and the performance of the first RL agent in generating said sub-goals for achieving the overall goal in the computer game environment.

The method may further comprise, freezing the state of the second RL agent whilst the first RL agent iteratively generates said sequence of sub-goals in the computer game environment for the frozen second RL agent to interact with and updating the first RL agent further comprising updating the state of the first RL agent based on a first reward issued when the frozen second RL agent successfully achieves the current sub-goal or times out in multiple attempts at achieving the current sub-goal, wherein said first reward is based on the performance of the frozen second RL agent attempting to achieve the current sub-goal.

The method may further comprise, freezing the state of the first RL agent whilst the second RL agent iteratively interacts with the computer game environment in relation to each sub-goal iteratively generated by the frozen first RL agent, wherein updating the second RL agent further comprising updating the state of the second RL agent based on one or more second rewards, each second reward issued by the computer game environment in relation to the performance of each attempt the second RL agent makes when interacting with the computer game environment to achieve the current sub-goal.

According to a second aspect of this specification, there is disclosed a generator RL apparatus for procedural content generation in a computer game environment of a video game, the apparatus including one or more processors and a memory, the memory comprising instructions that, when executed by the one or more processors, cause the apparatus to perform operations comprising: iteratively generating, using a trained generator RL agent trained using a reinforcement learning technique, each sub-goal in a sub-goal sequence within the computer game environment, the sub-goal sequence configured for meeting an overall goal in the computer game environment, wherein a trained solver RL agent or player interacts with the computer game environment in an attempt to achieve a current sub-goal in the sub-goal sequence and, when the trained solver RL agent or player successfully achieves the current sub-goal in the sub-goal sequence, the trained generator RL agent generates a new sub-goal for the sub-goal sequence until the overall goal is achieved by the trained solver RL agent or player; and updating the computer game environment based on each generated sub-goal for use by the trained solver RL agent or player.

According to a third aspect of this specification, there is disclosed a system for training a first RL agent and a second RL agent coupled to a computer game environment of a video game, the system comprising: a generation module for configuring a first RL agent to iteratively generate a sub-goal sequence in relation to an overall goal within the computer game environment, wherein the first RL agent module generates a new sub-goal for the sub-goal sequence after a second RL agent, interacting with the computer game environment, successfully achieves a current sub-goal in the sub-goal sequence; and an interaction module for configuring a second RL agent to iteratively interact with the computer game environment to achieve the current sub-goal, wherein each iterative interaction comprises an attempt by the second RL agent for interacting with the computer game environment to achieve the current sub-goal; a first update module for updating the first RL agent using a first reward issued when the second RL agent successfully achieves the current sub-goal; a second update module for updating the second RL agent using a second reward issued by the computer game environment based on the performance of the second RL agent attempting to achieve said current sub-goal; and an output module for outputting, once the first and second RL agents are validly trained, a final first RL agent for automatic procedural content generation, PCG, in the computer game environment, and a final second RL agent for automatically interacting with a PCG computer game environment.

According to a fourth aspect of this specification, there is disclosed a solver RL apparatus for interacting with a procedural content generated (PCG) computer game environment of a video game, the apparatus including one or more processors and a memory, the memory comprising instructions that, when executed by the one or more processors, cause the apparatus to perform operations comprising: iteratively interacting, using a trained solver or player RL agent trained using a reinforcement learning technique, with each sub-goal in a sub-goal sequence within the PCG computer game environment, the sub-goal sequence configured for meeting an overall goal in the computer game environment, wherein each sub-goal in the sub-goal sequence is generated by a trained generator RL agent in which the computer game environment is updated accordingly, and the solver RL agent or player interacting with the sub-goals in the computer game environment in an attempt to achieve a current sub-goal in the sub-goal sequence and, when the trained solver RL agent or player successfully achieves the current sub-goal in the sub-goal sequence, the trained generator RL agent generates a new sub-goal for the sub-goal sequence until the overall goal is achieved by the trained solver RL agent or player.

According to a fifth aspect of this specification, there is disclosed a generator RL apparatus for automatically generating a procedurally content generated computer game environment for a video game, the apparatus comprising a processor, a memory unit and a communication interface, wherein the processor is connected to the memory unit and the communication interface, wherein processor and memory are configured to implement a generator RL agent trained based on the computer-implemented method according to the first aspect.

According to a sixth aspect of this specification, there is disclosed a solver RL apparatus for automatically interacting with a procedurally content generated computer game environment of a video game, the apparatus comprising a processor, a memory unit and a communication interface, wherein the processor is connected to the memory unit and the communication interface, wherein processor and memory are configured to implement a solver RL agent or player agent trained based on the computer-implemented method according to the first aspect.

According to a seventh aspect of this specification, there is disclosed a non-transitory tangible computer-readable medium comprising data or instruction code for training a first RL agent and a second RL agent coupled to a computer game environment of a video game, which when executed on one or more processor(s), causes at least one of the one or more processor(s) to perform at least one of the steps of the method of: training, using RL techniques, a first RL agent for generating one or more portions of a computer game environment and a second RL agent for interacting with the one or more generated portions of the computer game environment, said training comprising: updating the first RL agent based on a first reward associated with the second RL agent successfully interacting with the generated portions of the computer game environment; and updating the second RL agent based on one or more second reward(s) received from the computer game environment associated with the performance of second RL agent iteratively interacting with the generated portions of the computer game environment; and outputting, when validly trained, a final first RL agent for automatic PCG of a computer game environment, and a final second RL agent for automatically interacting with a PCG computer game environment.

According to an eighth aspect of this specification, there is disclosed a non-transitory tangible computer-readable medium comprising data or instruction code for training a first RL agent and a second RL agent coupled to a computer game environment of a video game, which when executed on one or more processor(s), causes at least one of the one or more processor(s) to perform at least one or more of the steps of the computer-implemented method according to the first aspect.

BRIEF DESCRIPTION OF THE DRAWINGS

Embodiments of the invention will be described, by way of example, with reference to the following drawings, in which:

FIG. **1***a* is illustrates an example adversarial RL training system for training a first RL agent and a second RL agent in a computer game environment of a video game according to some embodiments of the invention;

FIG. **1***b* illustrates another example adversarial RL training system based on the adversarial RL training system of figure is according to some embodiments of the invention;

FIG. **1***c* illustrates an example RL training process for training the first and second RL agents in the adversarial RL training systems or of FIG. **1***a* or **1***b* according to some embodiments of the invention;

FIG. **2***a* illustrates an example iterative Generator RL training process for use in steps **122** and **124** of the RL training process of FIG. **1***c* and by adversarial RL training systems **100** or **110** according to some embodiments of the invention;

FIG. **2***b* illustrates an example iterative Solver RL training process for use in steps **122** and **124** of the RL training process of FIG. **1***c* and by adversarial RL training systems **100** or **110** according to some embodiments of the invention;

FIG. **3** illustrates an example First Person Shooter (FPS) platform game for training a Generator and Solver according to some embodiments of the invention;

FIG. **4** illustrates an example FPS platform computer game environment output from a trained Generator according to some embodiments of the invention;

FIG. **5** illustrates an example outputs of a trained Generator for the FPS platform computer game of FIGS. **4** and **5** when varying the auxiliary diversity input value/signal input to the trained Generator according to some embodiments of the invention;

FIG. **6** illustrates an example Racing game for training a Generator and Solver according to some embodiments of the invention;

FIG. **7** illustrates an example Racing computer game environment output from a trained Generator according to some embodiments of the invention;

FIG. **8** illustrates an example outputs of a trained Generator for the Racing computer game of FIGS. **6** and **7** when varying the auxiliary diversity input value/signal input to the trained Generator according to some embodiments of the invention;

FIG. **9** illustrates an example performance table in relation to differently trained Solver agents on unseen Racing computer game environments generated by a trained Generator according to some embodiments of the invention;

FIG. **10** illustrates an example performance table in relation to differently trained Solver agents on unseen FPS Platform computer game environments generated by a trained Generator according to some embodiments of the invention;

FIG. **11** illustrates another example table for comparing the performance of differently trained Solver agents on unseen FPS Platform/Racing computer game environments generated by a trained Generator according to some embodiments of the invention; and

FIG. **12** is a schematic diagram of a computing system according to some embodiments of the invention.

Common reference numerals are used throughout the figures to indicate similar features.

DETAILED DESCRIPTION

FIG. **1***a* illustrates an example adversarial RL training system **100** for training a first RL agent **102** and a second RL agent **104** in a computer game environment **106** of a video game. The first RL agent **102** is trained to generate game environment data **103** for updating the computer game environment **106** of the video game. The computer game environment **106** may be any type of computer game environment such as, without limitation, for example a two-dimensional and/or a three-dimensional game environment. The generated game environment data **103** is associated with one or more sub-goals of an overall goal set by the first RL agent **102** (also referred to herein as a so-called Generator or Generator RL agent), where the second RL agent **104** (also referred to herein as a so-called Solver or Solver RL agent) interacts with the updated computer game environment **106** for achieving said one or more sub-goals and/or the overall goal. The second RL agent **104** is trained to interact with the updated computer game environment **106** in relation the generated environment data **103** of the computer game environment **106** to achieve said one or more sub-goals and/or the overall goal. Once trained, the resulting first and second RL agents **102** and **104** of the adversarial RL system too may be used for procedural content generation (PCG) of the computer game environment **106** and automatically interacting with PCG computer game environments, respectively.

The Generator and Solver RL agents **102** and **104** co-exist as adversarial agents where the Generator **102** creates a game environment data **103** (e.g. racing tracks, platforms, paths, etc.) associated with one or more sub-goals of an overall goal (e.g. completing the racing track, traversing a set of platforms or paths, etc.) for a computer game environment **106** which the Solver **104** is tasked to solve/traverse to achieve said one or more sub-goals of the overall goal. The Solver **104** may provide feedback **102***b* (or direct **102***c*) to the Generator **102** in the form of observations and rewards **102***b* via the computer game environment **106** (or directly via optional reward **102***c*). In response, the Generator **102** challenges the Solver **104** by creating an adapted problem such as new sub-goals of the overall goal. This way the system too is symbiotic as without the Solver **104** the Generator **102** would not be able to create game environment data **103** for the computer game environment **106** that is "playable" (or solvable by a player or user), and the Solver **104** without the Generator **102** would not be able to generalize or adapt well over unseen computer game environments. The use-cases for this adversarial RL system too includes: 1) Training a first RL agent (e.g. Generator) **102** to make the second RL agent **104** (e.g. Solver) fail, which makes the second RL agent (e.g. Solver) **104** more robust; and 2) The first RL agent **102** (e.g. Generator) can be used to generate new game environment data **103** and hence creating new computer game environments **106** which are shown to be traversable or solvable and the like by the second RL agent **104** (e.g. Solver) and hence by a user or player (if traversed by the Solver).

The adversarial RL system **100** uses adversarial deep RL techniques for training the first RL agent **102** (also referred to herein as a so-called Generator or Generator RL agent) for generating game environment data **103** for a PCG computer game environment **106**, and for training at least one second RL agent **104** (also referred to herein as a so-called Solver/Player or Solver/Player RL agent) for interacting with the PCG computer game environment **106** for solving/traversing the sub-goals and/or overall goals associated with the game environment data **103** generated by the Generator RL agent **102** for said PCG computer game environment **106**. The sub-goals and/or overall goals are set by the Generator RL agent **102** when generating computer game environment data **103** for said PCG computer game environment **104**.

For example, game environment data **103** associated with one or more sub-goals in the computer game environment **106** may include data representative of one or more objects within the computer game environment **106** to be interacted with by the second RL agent **104** in the computer game environment **106**. In another example, game environment data **103** associated with one or more sub-goals may include data representative of a segment of a track or path within the computer game environment **106** to be traversed by the second RL agent **104** in the computer game environment **106**. In another example, game environment data **103** associated with one or more sub-goals in the computer game environment **106** may include data representative of a section or portion of the computer game environment to be solved or traversed by the second RL agent **102** in the computer game environment **106**. In essence, the game environment data **103** generated by the Generator RL agent **102** includes any type of game environment data that is used to modify or update the computer game environment **106** to cause the Solver RL agent **104** to interact with the computer game environment **106** and successfully achieve one or more sub-goals and/or an overall goal associated with the generated game environment data **103**.

The first RL agent/Generator RL agent **102** may be any RL agent suitable for generating game environment data **103** for setting one or more sub-goals and/or overall goals within the computer game environment **106** for achieving by a second RL agent/Solver RL agent **104** during its interactions with the computer game environment **106**. The first RL agent/Generator RL agent **102** is capable of being trained using reinforcement learning techniques. For example, the Generator RL agent **102** may be based on any of: a policy function; an actor-critic model; or a Q-function. The Generator RL agent may be implemented by, without limitation, for example a Feed Forward neural network (FFNN), Long Short-term memory (LSTM) model or Gated Recurrent Unit (GRU) based artificial neural network (ANN), such as a recurrent neural network (RNN). Many other alternatives will be apparent to those skilled in the art.

The second RL agent/Solver RL agent **104** may be any RL agent suitable for controlling the actions **104***a* of a playable character **105** or object, non-playable character or object, or other interactive object **105** in a computer game environment in which the Solver RL agent **104** is capable of being trained using reinforcement learning techniques. For example, the Solver RL agent **104** may be based on any of: a policy function; an actor-critic model; or a Q-function. The Solver RL agent **104** may be implemented by, without limitation, for example a Feed Forward neural network (FFNN), a Long Short-term memory (LSTM) model or Gated Recurrent Unit (GRU) based artificial neural network (ANN), such as a recurrent neural network (RNN). Many other alternatives will be apparent to those skilled in the art.

For example, the first and second RL agents may each include a neural network with at least two interconnected layers in which each layer includes a plurality of neural units connected together. Each neural network may be a feed forward neural network. The RL technique used for training and updating the state of the neural networks of the first and second RL agents may be based on one or more proximal policy optimisation algorithms and the like.

The first RL agent/Generator RL agent **102** is configured to create and output actions iota corresponding to generated game environment data **103** in response to receiving a first reward **102***b* associated with the performance of the second RL agent/Solver agent **104** interacting with the computer game environment **104** when attempting to achieve said one or more sub-goals or the overall goal. The output actions **102***a* are used to update the computer game environment **106**. The first Generator RL agent **102** may also receive game environment data observations associated with the Solver RL agent **104** interactions with the computer game environment **106**. The first RL agent/Generator RL agent **102** outputs the actions **102***a* of generated game environment data **103** associated with a new sub-goal for updating the computer game environment **106** and causing the second RL agent **104** associated with a player character **105** and the like in the computer game environment **106** to perform one or more further actions **104***a* controlling the player character **105** and the like to achieve the new sub-goal.

The second RL agent/Solver RL agent **104** is configured to create and outputs actions **104***a* for controlling a player character **105** to the computer game environment **106** in response to receiving a second reward **104***b* and game environment observations from the computer game environment **106** based on previous output actions **104***a*. The output actions **104***a* enables the second RL agent **104** to control a player character **105** and the like in the computer game environment to achieve or attempt to achieve the current sub-goal, one or more sub-goals, and/or the overall goal set by the Generator RL agent **102**. The Solver RL agent **104** receives the second reward **104***b* based on the performance of the Solver agent **104** in achieving the current sub-goal when interacting via the player character **105** with the computer game environment **104**. The output actions **104***a* are used to control the actions of a player character **105** in the computer game environment **106**.

The interactions of the Solver RL agent **104** is governed by a set of actions for controlling a player character **105** and the like in the computer game environment **106**. For example, this may enable the Solver RL agent **104** to control the player character **105** to solve one or more portions of the computer game environment **106** to achieve the current sub-goal. In another example, this may enable the Solver RL agent to control the player character and the like **105** to traverse the computer game environment **106** to achieve the current sub-goal. As another example, the set of actions may be output as player action data **104***a* for causing a player character **105** in the computer game environment **106** to perform the one or more actions associated with the player action data **104***a* and achieve or attempt to achieve the current sub-goal.

The Generator **102** receives a reward from a Generator reward function that is based on an internal generator reward and an external generator reward. The external generator reward may be received as the first reward **102***b* from the computer game environment **106** and/or, as an option, received as a first reward **102***c* from the Solver **104**. The internal generator reward is dependent on the actions of the Generator **102**. The external generator reward **102***b* is tied to the performance of the Solver when interacting with the computer game environment **106** for achieving the one or more sub-goals and/or overall goal set by the game environment data **103** created by the Generator **102**. The Generator reward function is mainly based on the performance on progression and failure but it can be set differently depending on the desired behaviour of the Generator **102**. In order to train a Generator **102** to create a challenging environment there is always a balance to strike between trivial and impossible computer game environments **106**. The Generator reward function is configured and designed to mainly drive between two extremes in relation to progress and behaviour. At one extreme, the Generator **102** should generate game environments **103** that help the Solver **104** reach the sub-goals and/or overall goal (e.g. progress), and on the other extreme, the Generator **102** should actively try to make the Solver **104** behave "sub-optimally" (i.e. any deviation from the fastest-path to goal could be considered sub-optimal, but this is also where the behaviour is manifested).

The Solver **104** also receives a reward from a Solver reward function that is based on an internal solver reward and an external solver reward. The external solver reward may be received as the second reward **104***b* from the computer game environment **106**. The internal solver reward is dependent on the actions of the Solver **104**. The external solver reward **104***b* is tied to the performance of the Solver when interacting with the computer game environment **106** for achieving the one or more sub-goals and/or overall goal set by the game environment data **103** created by the Generator **102**. Generally, the Solver reward function for the Solver contains a progressive reward, plus a negative for failing. The negative reward for failing is important to have as it stops the Solver **104** from generating actions that control the player character **105** for taking too "big a risk" and consequently forcing the Generator **102** to create game environment data **103** that is not impossible.

During training of the adversarial RL system **100**, the Generator **102** receives a first reward signal **102***b* from the computer game environment **106** based on the performance of the Solver **104** interacting with the computer game environment **106** which encourages the design of computer game environment **106** to be challenging, but not impossible, whilst the Solver **104** receives a second reward signal **104***b* based on its performance interacting in the computer game environment **106** designed and generated by the Generator **102**. This provides the advantages of the Solver **104** achieving better generalization through a plethora of generated challenges from the Generator **102**, whilst the Generator **102** is able to better create game environment data **103** for diverse PCG computer game environments that are playable/solvable by the Solver **104**. The resulting trained first RL agent or Generator **102** is configured for generating PCG computer game environments **106** and the resulting trained second RL agent or Solver **104** is configured for interacting with PCG computer game environments. As an option, such a trained Generator **102** and Solver **104** can be used for assisting game designers in robustly designing and testing PCG computer game environments.

FIG. **11***a* illustrates another example adversarial RL training system **110** based on the adversarial RL training system too of FIG. **1***a*. The adversarial RL training system **110** is configured for training the first RL agent/Generator **102** and second RL agent/Solver **104** in the computer game environment **106** of a video game. The adversarial RL training system **110** has modified the adversarial RL training system too by including auxiliary diversity input signals **112***a* and **112***b*, which are input to the Generator **102** and the computer game environment **106**. The auxiliary diversity input signals **112***a* and **112***b* are coupled to the Generator reward function of the Generator **102** and to the reward function of the computer environment **106**, respectively. The reward function of the computer environment **106** is used to generate the first reward **102***b* (or by the Solver when generating reward **102***c*). As the auxiliary input signals **112***a* and **112***b* are connected to the Generator reward function and the reward function of the computer game environment **106** associated with the Generator **102**, they are used as a training enhancer and can also be used to indirectly control the game environment data **103** output of the trained Generator **102** (also referred to as a Generator model).

Generally, when training the Generator **102** there is a balance to be struck between impossible and trivial computer game environments **106**, the auxiliary diversity input signals **112***a* and **112***b* enables this balance to be controlled externally by a game designer and/or user. In addition, training an adversary RL based Generator **102** against a RL based Solver agent **104** may lead to convergence to the optimal utility function for both Generator and Solver agents **102** and **104**. This may be undesirable because: 1) the solutions may lead to low generalization ability for the Solver **104**, and the Generator **102** then allows for little control. Thus, with the auxiliary diversity input signal **112***a* and **112***b* connected to the Generator network and the computer game environment **106**, the difficulty and/or diversity of the Generator **102** may be controlled, which also results in trained Solver agents **104** that are generalizable.

The auxiliary diversity input signal **112***a* is used to control the Generator reward function in such a way that the output of the Generator **102** may be controlled indirectly. In this manner, the Solver **104** is confronted with varying difficulty and behaviour (controlled by auxiliary diversity input signal **112***a* to the Generator **102**) which increases its generalization ability to solve previously unseen computer game environments. The output behaviour of the Generator **102** changes when the auxiliary diversity input signal **112***a* (and **112***b*) is changed.

The auxiliary diversity input signal **112***a* is applied to the Generator reward function of the Generator **102**. As previously described, the Generator reward function of the Generator is a combination of an external generator reward and an internal generator reward. The external generator reward is based on the first reward **102***b* from the computer game environment **106** (or optionally from the Solver **104** via reward **102***c*). The internal generator reward is based on the auxiliary diversity signal **112***a* and the performance of the Generator **102** in generating said game environment data **103** and corresponding sub-goals for achieving the overall goal in the computer game environment **106**.

The auxiliary diversity input signals **112***a* and **112***b* are used to further drive diversity, generalisability and control of the generation of game environment data **103** for updating the computer game environment **106**. The connection of the auxiliary diversity input signals **112***a* and **112***b* to the corresponding reward functions causes the Generator **102** to generate game environment data **103** that results in previously unseen computer game environments. A game designer may use the auxiliary diversity input signals **112***a* and **112***b* as a control variable to control the difficulty and/or diversity of the Generator's output **103**.

The auxiliary diversity input signals **112***a* and **112***b* have the same value. The auxiliary diversity signals **112***a* and **112***b* may each have the same value within a range between a negative auxiliary threshold value and a positive auxiliary threshold value (ATH). For example, auxiliary diversity signals **112***a* and **112***b* may be assigned the same value within the range of [**−1**, **1**].

An example Generator reward function with auxiliary scaling may be based on:

$$r=r_i\lambda_{A_i}\alpha+r_e\lambda_{A_i}\beta.$$

where λ_{A_i}, $\in[-1;1]$ is fed in as input to the network in the form of an observation, r_i/r_e is the internal/external generator rewards, and λ_{A_i} the auxiliary diversity input signal **112***a*, with α; β being weighting factors. Although the auxiliary input diversity signal **112***a* is described as being $\lambda_{A_i}\in[-1;1]$, this is by way of example only, the skilled person would appreciate that $\lambda_{A_i}\in[-ATH;ATH]$, where ATH may be an auxiliary threshold value (ATH), which may be a non-zero real value or integer greater than zero.

The adversarial RL training system **110** provides the advantage of training a Generator **102** and/or creating a trained Generator **102** that is capable of providing training data to a Solver **104** that enables the Solver **104** to handle all/most environments produced by the Generator **102** and all/most environments authored by a human (e.g., game developer, player). The adversarial RL training system **110** also provides the advantage of creating a trained Generator **102** that can assist game designers in creating environments that could be controlled and quantified by designed metrics by adjusting the auxiliary diversity input signals **112***a* and/or **112***b* (e.g. such as varying the difficulty and/or diversity of the computer game environment **106**). The adversarial RL training system **110** also provides the advantage of creating a trained Solver **104** that is adaptable and/or generalizable enough to assist game designers to test unseen computer game environments in real-time production.

FIG. **1***c* illustrates an example RL training process **120** for training the first and second RL agents in the adversarial RL training systems **100** or **110** of FIG. **1***a* or **1***b*. The Generator and Solvers **102** and **104** are trained with a version of self-play in which the Generator **102** and Solver **104** are trained in an iterative fashion one after the other and/or concurrently, with the training of the Solver **104** occurring at a higher frequency compared to that of the Generator **102**. It is noted, that the training of the Generator **102** and Solver **104** is not a zero-sum game, where the gain of one is the loss of the other proportionally. Rather, the training of the Generator **102** and Solver **104** is a semi-collaborative game where there are elements of competition but also collaboration. This reduces the risk for exploits being developed by either the Generator or Solver **102** or **104** whilst more substantial/relevant challenges may be posed. The RL training process **120** may include the following steps of:

In step **122**, iteratively generating, by the Generator **102**, game environment data representative of a sub-goal sequence in relation to an overall goal within the computer game environment **106**, which may include the following steps of: In **122***a* generating game environment data **103** representative of a new sub-goal for the sub-goal sequence after the Solver **104**, interacting with the computer game environment **106**, successfully achieves a current sub-goal in the sub-goal sequence. The computer game environment **106** may be updated based on the generated game environment data **103**. In step **122***b*, updating the Generator **102** using a first reward **102***b* issued when the Solver **104** successfully achieves the current sub-goal. The first reward **102***b* may be issued by the computer game environment **106**.

In step **124**, iteratively interacting, by the Solver **104**, with the computer game environment **106** to achieve a current sub-goal based on the following steps of: In step **124***a*, performing one or more actions, by the Solver **104**, in the computer game environment **106** to achieve the current sub-goal. In step **124***b*, updating the Solver **104** using a second reward **104***b* issued by the computer game environment **106** based on the performance of the second RL agent attempting to achieve said current sub-goal.

In step **126**, determining whether the Generator **102** and/or the Solver **104** have been validly trained. This may include the Solver **104** achieving a particular predetermined average success rate in relation to the generated game environment data **103** representative of each new sub-goal and/or sub-goal sequences and/or overall goals set by the Generator **102**. This may include the Solver **104** and Generator **102** having been trained for a predetermined number of episodes/overall goals and the like. If the Generator **102** and the Solver **104** have been validly trained (e.g. "Y"), then the process **120** proceeds to step **128**. Otherwise, if either the Generator **102** or the Solver **104** are not validly trained (e.g. "N"), or a maximum number of iterations have not been achieved thereto, then the process **120** proceeds to steps **122** or **124** for further training in relation to further game environment data representative of one or more new sub-goals, or new overall goals, episodes and the like in relation to the computer game environment **106**.

In step **128**, outputting, once validly trained, a final Generator **102** or Generator model for use in automatic procedural content generation (PCG) in the computer game environment, and outputting a final Solver **104** or Solver model for automatically interacting with a PCG computer game environment.

As an option, the frequency of performing step **124** for iteratively training the Solver **104** and updating the Solver **104** based on the Solver **104** iteratively interacting with the computer game environment **106** in relation to the current sub-goal is greater than the frequency of performing step **122** for iteratively training the Generator **102** and updating the Generator **102** based on the Generator **102** iteratively generating game environment data **103** representative of each sub-goal in the sequence of sub-goals towards the overall goal in the computer game environment **106**.

The Generator **102** may be configured to iteratively generate the game environment data representative of each sub-goal of the sub-goal sequence in an iterative manner rather than generating all of the game environment data of the entire sub-goal sequence at once. That is, the Generator **102** performs an iterative creation process of the game environment data **103** one new sub-goal and/or one new overall goal at a time (e.g. one new sub-goal per iteration) rather than generating the whole computer game environment with overall goal at once. Thus, the adversarial RL Generator (e.g. ARLPCG) generates the whole computer game environment from scratch in an iterative fashion. One advantage with this approach is that the Generator **102** does not create new game environment data **103** representative of a new sub-goal (e.g. a new section/segment of the computer game environment **106**) until after the Solver **104** achieves the current sub-goal (e.g. reaches the latest section/segment of the computer game environment **106**), so the Generator **102** always creates a solvable new sub-goal (e.g. solvable reachable segment) for the playing character **105**.

FIGS. **2***a* and **2***b* illustrates an example iterative Generator RL training process **200** and iterative Solver RL training process **220** for use in steps **122** and **124** of the RL training process **110** of FIG. **1***c* and by adversarial RL training systems **100** or **110**. As previously described with reference to FIG. **1***c*, the Generator **102** and Solver **102** may be trained with a version of self-play, where the Generator **102** and Solver **104** are trained in an iterative fashion. In the example of FIG. **2***a*, the Generator **102** is trained in an iterative fashion with the state of the Solver network being frozen (i.e. only running inference) when the training Generator network is iteratively generating game environment data and/or updating. In the example of FIG. **2***b*, the Solver **104** is trained in an iterative fashion with the state of the Generator network being frozen (i.e. only running inference) when the training Solver network is iteratively interacting and/or updating.

Referring to FIG. **2***a*, the iterative Generator RL training process **200** may include the following steps of, where the state of the Solver network is frozen: In step **202**, generating, by the Generator **102**, game environment data **103** representative of a sub-goal in relation to an overall goal within the computer game environment **106**. The computer game environment **106** is updated based on the generated game environment data **103**, the generated sub-goal becomes the current sub-goal. In step **204**, running inference by the frozen Solver **104**, in which the Solver iteratively interacts with the computer game environment **106** to achieve the current sub-goal until the frozen Solver **104** successfully achieves the current sub-goal and/or times out in multiple attempts at achieving the current sub-goal. In step **206**, receiving a first reward **102***b* based on the performance of the frozen Solver **104** in achieving the current sub-goal. In step **208**, updating the network of the Generator **102** based on using the first reward **102***b*. In step **210**, determining whether the overall goal has been achieved by the Generator **102** and/or the Solver **104**. If the overall goal has been achieved by the Generator **102** (e.g. "Y"), then proceeding to step **212**, otherwise the process **200** proceeds to step **202** for generating a next/new sub-goal towards achieving the overall goal. In step **212**, determining whether the Generator network is validly trained, and proceeding to step **216** if the Generator network is validly trained (e.g. success rate has been achieved, max number of training iterations has been achieved), otherwise proceeding to step **214** if the Generator network is not validly trained. In step **214**, generating a new overall goal/episode, as the current overall goal has been generated by the Generator **102**, proceeding to step **202** for generating a new sub-goal towards the new overall goal. In step **216**, outputting a final RL agent representative of the trained Generator **102** or Generator model, where the trained Generator **102** may be used for automatic PCG for computer game environments.

Referring to FIG. **2***b*, the iterative Solver RL training process **220** may include the following steps of, where the state of the Generator network is frozen: In step **222**, running inference by the frozen Generator **102** by generating game environment data **103** representative of a sub-goal in relation to an overall goal within the computer game environment **106**. The computer game environment **106** is updated based on the generated game environment data **103**, the generated sub-goal becomes the current sub-goal. In step **224**, interacting, by the Solver **104**, with the computer game environment **106** to achieve the current sub-goal. In step **226**, receiving a second reward **104***b* based on the performance of the Solver **104** in achieving the current sub-goal. In step **228**, updating the network of the Solver **104** based on using the second reward **104***b*. In step **230**, determining whether the Solver **104** successfully achieved the current sub-goal and/or timed out in multiple attempts/iterations at achieving the current sub-goal. If the current sub-goal is successfully achieved or the Solver has timed-out i.e. a maximum number of iterations for attempting to achieve the current sub-goal has been reached (e.g. "Y"), then proceeding to step **232**, otherwise, if current sub-goal not achieved and Solver **104** not timed-out (e.g. "N"), proceeding to step **224** for interacting with the computer game environment **106** to achieve said current sub-goal. In step **232**, determining whether the overall goal has been achieved by the Solver **104**, if overall goal has been achieved by the Solver **104** (e.g. "Y") then proceed to step **234**, otherwise (e.g. "N") proceed to step **222** for the frozen Generator **102** to generate a new sub-goal towards achieving the overall goal. In step **234**, determining whether the Solver network is validly trained, and proceeding to step **238** if the Solver network is validly trained (e.g. success rate has been achieved, max number of training iterations has been achieved), otherwise proceeding to step **236** if the Solver network is not validly trained. In step **226**, generating a new overall goal/episode by the frozen Generator **102**, as the current overall goal has been generated by the Generator **102**, proceeding to step **222** for generating a new sub-goal towards the new overall goal. In step **238**, outputting a final RL agent representative of the trained Solver **104** or Solver model, where the trained Solver **104** may be used for automatically interacting with a PCG computer game environment and the like.

The iterative Generator RL training process **200** may be performed in step **122** of RL training process **120** of FIG. **1***c*, and the iterative Solver RL training process **220** may be performed in step **124** of RL training process **120** of FIG. **1***c*. Furthermore, within RL training process **120**, the iterative Solver RL training process **220** of the Solver **104** may operate at a higher frequency that the iterative Generator RL training process **200**, where the iterative Solver RL training process **220** performs hundreds of actions per episode with corresponding updates to the Solver network (e.g. generating actions **104***a* for controlling a player character **105**), while the iterative Generator RL training process **200** completes actions **102**_a_ and updates to the Generator network (e.g. generating new game environment data **103**) in the order of dozens. For example, the switch between iterative Generator RL training process **200** (e.g. step **122** of FIG. **1**_c_) and the iterative Solver RL training process **220** may occur, without limitation, for example at a frequency of about a tenth for the iterative Generator RL training process **200** compared with the iterative Solver RL training process **220**. Further fine-tuning of the trained Generator or trained Solver may be performed, if necessary, on either the Generator network or Solver network with the other RL agent network (e.g. Solver or Generator networks, respectively) being frozen and running inference only.

Further modifications to the adversarial RL training systems **100** and/or **110** and training RL process **120** of FIGS. **1**_a_-**1**_c_ and Generator/Solve RL processes **200** and **220** of FIGS. **2**_a_ and **2**_b_ may also include, rather than training one Solver **104** per Generator **102**, training a population of Solvers **104** with said Generator **102**. This may provide the advantage of further improving the diversity of the Generator's **102** output as it would be harder for the Generator **102** to exploit the behaviour of the population of Solvers **104**, whilst improving the generalisability of the population of Solvers **104**.

FIGS. **3** to **5** and FIGS. **6** to **8** illustrates examples of two types of 3D computer game environment that may be used with the adversarial RL training systems **100** or **110** for training a Generator **102** and Solver **104** based on using RL training processes **120**, **200** and/or **220** as described with reference to FIGS. **1**_a_ to **2**_b_. The types of example 3D computer game environments include, without limitation, for example a First Person Shooter (FPS) Platform game (also referred to as a FPS Platform game or Platform game) as described with reference to FIGS. **3** to **5** and a Racing (RC) game as described with reference to FIGS. **6** to **8**. These are used for illustrating the operation and performance of the resulting trained Generator **102** and Solver **104** output from adversarial RL training system **110** with auxiliary diversity input signals **112**_a_ and **112**_b_ applied thereto. Although the example 3D computer game environments described herein are based on only two popular game genres, this is by way of example only and this disclosure is not so limited, it is to be appreciated by the skilled person that the adversarial RL training systems **100**, **110** with or without auxiliary diversity input signals **112**_a_ and **112**_b_ for training a Generator **102** and a training a Solver **104** may be applied to any type of 2D and/or 3D computer game environment as the application demands.

In these examples, the Generator **102** parameterizes the corresponding game environment data **103** one goal at a time (e.g. segment by segment, platform by platform) in an iterative manner when outputting the generating game environment data **103** along with control parameters and the like. In both environments, an auxiliary diversity input value **112**_a_/**112**_b_ is applied to the Generator **102** and the computer game environment **106** during training, so when the auxiliary diversity input value is negative the Generator **102** receives a small negative reward per time step or iteration. The idea behind this setup is that the "ticking" negative values force the Generator **102** to create an environment that the Solver **104** either (depending on the auxiliary task) finishes and is successful, or fails fast. Thus, if the auxiliary diversity input value **112**_a_/**112**_b_ is low or negative, the Generator **102** will design/create game environment data **103** for updating the computer game environment **106** that is difficult while if the auxiliary diversity input value is high and/or positive the Generator **102** should design/create game environment data **103** that is easier for the Solver **104** and associated player character to traverse. Independent on the auxiliary diversity input value the Generator **102** also receives an incremental reward for the Solver's performance or progress towards one or more sub-goals and/or the overall goal (e.g. when the Solver **104** controls the player character closer to each predefined goal and/or the overall predefined goal). In the training, the overall goal positions within each game environment are randomized to further ensure that diversity in training, but also to train the Generator **102** to create a path or one or more game portions that achieve the predefined final goal/position set by a game designer. In these examples, the FPS and RC games are built in Unity® and connected to the adversarial RL training system **110** and computer game environment **106** using the so-called ML Agents API in Unity.

FIG. **3** illustrates an example FPS platform game **300** in which the Generator **102** (e.g. first RL agent) is trained to generate and output game environment data **310** for updating the computer game environment **106** of the Platform game **300**, and the Solver **104** (e.g. second RL agent) is trained to interact with the computer game environment **106** of the Platform game **300** and output a set of actions for controlling a player character **305** in the Platform game **300**. In the Platform game **300**, the Solver **104** or a player controls a player character **305** with the overall goal of traversing as fast as possible to maximize reward along a generated track of a plurality of platform segment blocks **312**_a_-**312**_b_ placed within the computer game environment **106** of the Platform game **300**.

In this example, the Generator **104** is configured to generate/create game environment data **310** including platform segment blocks **312**_a_-**312**_b_ and actions **314**_a_-**314**_d_ associated with each of the blocks **312**_a_-**312**_b_ that are representative of sub-goals that lead towards an overall goal (e.g. a final platform block) within the Platform game **300**. Each of the sub-goals are represented by each of the platform segment blocks **312**_a_-**312**_b_ and actions controlling the characteristics of each platform segment block **312**_a_-**312**_b_ including, without limitation, for example distance **314**_a_ between platform segment blocks **312**_a_-**312**_b_, angle of orientation **314**_b_ of platform segment **312**_a_, and height **314**_c_ of each platform segment **312**_a_ relative to the next platform block **312**_b_ or a previous platform segment block, and also size **314**_d_ of each platform segment block **312**_a_ and any other suitable action for controlling the characteristics or features of the blocks **312**_a_-**312**_b_ as the application demands and the like. The Solver **104** is configured to interact with the computer game environment **106** of the Platform game **300** by controlling the player character **305** to achieve each of the sub-goals represented by each of the platform blocks **312**_a_-**312**_b_ and/or overall goal represented by the final sub-goal in the sub-goal sequence using a set of actions based on, without limitation, for example forward/backward actions **306**_a_, turn actions **306**_b_, and jumping actions **306**_c_, and any other suitable action for controlling the player character **305** as the application demands and the like.

In this example, the Generator **102** includes a Generator network based on a feed forward neural network with at least 2 hidden layers and 512 neural units per layer, with a hyperparameter γ of 0.990. The RL technique used for training the Generator **102** is based on, without limitation, for example a Proximal Policy Optimization (PPO) algorithm and the like with a learning rate of 2e-4. The Generator **104** receives a first reward **102**_b_ from the computer game environment **106** of the Platform game **300** along with observation data in the form of a state vector. The observation data provided by the computer game environment **106** of the Platform game **300** to the Generator **102** consists of a game state array or vector including data representative of the relative position to the overall goal, angle relative to the overall goal, overall goal distance, previous block position, size, and rotation, and auxiliary diversity input value and the like.

In this example, the Solver **104** includes a Solver network based on a feed forward neural network with at least 2 hidden layers and 512 neural units, with hyperparameter γ of 0.990. The RL technique used for training the Solver **104** is based on, without limitation, for example a PPO algorithm and the like with a learning rate of 3e-4. The Solver **104** receives a second reward **104***b* from the computer game environment **106** of the Platform game **300** along with observation data based on a ray cast and state vector for navigating around obstacles within the computer game environment **106**. For example, in the Platform game **300** the observation data may include a height map ray cast around the player character **305** of the Solver **104** for use by the Solver **104** to keep track of where the player character **305** is in relation to the platform segments representing sub-goals and/or overall goal and the like.

As an example, the Generator **102** is trained and configured to generate game environment data **310** that includes platform segment blocks with actions controlling the distance to next block (e.g. [5 m, 10 m]), the angle relative to the last two blocks (e.g. in degrees [−180, 180]), each block size (e.g. in metres [4 m, 6 m]), and height change (e.g. in metres [−2 m, 2 m]). The Solver **104** is trained and configured to control the actions of the player character **305** by inputting a set of actions **14***a* based on forward/backward, left/right turn, and jump actions to the computer game environment **106** of the Platform game **300**.

The Generator **102** and Solver **104** are trained based on the RL training processes **120**, **200** and/or **220** as described with reference to FIGS. **1***a* to **2***b*. For example, as previously described, the Generator **102** and Solver **104** may be trained with a version of self-play, where the Generator **102** and Solver **104** are trained in an iterative fashion. For example, in the Generator RL training process **200** of FIG. **2***a*, the Generator **102** is trained in an iterative fashion with the state of the Solver network being frozen (i.e. only running inference) with the Generator network iteratively generates game environment data, receiving the first reward **102***b*, and/or the network being updated accordingly. In the Solver RL training process **220** of FIG. **2***b*, the Solver **104** is trained in an iterative fashion with the state of the Generator network being frozen (i.e. only running inference) with the Solver network iteratively interacting with the computer game environment **106**, receiving second reward **104***b* and/or the network being updated accordingly.

During training, the Solver **104** receives a positive or negative reward from the Solver reward function based on a second reward **104***b* from the computer game environment **106** of the Platform game **300**. The Solver **104** may receive a positive reward based on the player character **305** moving towards the sub-goal, moving towards the overall goal, the time it takes to achieve a sub-goal/overall goal, and/or for completing the track or sequence of sub-goals. The Solver **104** receives a negative reward for failing to achieve each sub-goal and/or the overall goal, e.g. when the player character **305** falls off a platform segment or times out when attempting to complete the sub-goal associated with platform segment or overall goal associated with a plurality of platform segments. Generally, the reward function for the Solver **104** contains a progressive reward, plus a negative reward for failing. The negative reward for failing is important to have as it stops the Solver **104** from taking too "big a risk" when selecting the set of actions **104***a* for controlling the player character **305** and consequently forces the Generator **102** to create an computer game environment that is not impossible.

During training, the Generator **102** also receives a negative/positive reward from the Generator reward function, which may be based on the Solver **104** failing and is also dependent on the first reward **102***b* from the computer game environment **106** and the auxiliary diversity input value **112***a*. The Generator reward function with auxiliary scaling is based on $r=r_i\lambda_{A_i}\alpha+r_e\lambda_{A_i}\beta$ and is fed in as input to the Generator network in the form of an observation, the auxiliary diversity input signal **112***a*, r_i/r_e are the internal/external generator rewards in which the external generator reward is the first reward **102***b* received from the computer game environment **106**, with α; β being weighting factors that are adjusted by the designer of the game. The computer game environment **106** also receives the auxiliary diversity input signal **112***b*, which is the same as auxiliary diversity input signal **112***a*, and where the first reward **102***b* is based on the auxiliary diversity input value **112***b* and is connected to Solver's **104** failure primarily. For example, when the auxiliary diversity input signal is set to $\lambda_{A_i}=-1$ the failing of the Solver **104** is positively rewarding the Generator **102**, where the computer game environment **106** reward function may generate a first reward **102***b* value in the region of, without limitation, for example 10. In another example, when the auxiliary diversity input signal is set to $\lambda_{A_i}=1$ the failing of the Solver **104** is negatively rewarding the Generator **102**, where the computer game environment **106** reward function may generate a first reward **102***b* value in the region of, without limitation, for example −10.

FIG. **4** illustrates an example Platform game environment **400** in which a path is represented by game environment data **402***a*-**404***k*, **404** was generated by the trained Generator **102**. In this example, the Generator **102** was trained as described with reference to FIG. **3** and configured to learn how to create a path to an overall goal represented by platform segment block **404** from an initial start platform segment block **402***a*. In this case, the Generator **102** learned to iteratively create a path of sub-goals represented by platform segment blocks **402***a*-**402***k* towards a randomly generated overall goal represented by checkered platform segment block **404**, whilst at the same time it allowed the Solver **104** to traverse each platform segment block and achieve the corresponding sub-goal represented by it. The overall goal was far above the initial start platform segment block **402***a*, e.g. a simulated 20 metres in the computer game environment **400**, which resulted in the Generator **102** iteratively creating a sequence of sub-goals, each sub-goal represented by the plurality of platform segment blocks **402***a*-**402***k*, and **404**, which forms a "spiral staircase" from the start platform block position **402***a* to the overall goal represented by the checkered platform segment block **404**. The Solver **104** is configured to interact with the Platform game environment **400** and the game environment data **402***a*-**404** therein to control a player character **305** of FIG. **3** to traverse the "spiral staircase".

FIG. **5** illustrates further example Platform computer game environments **502** and **512** when the auxiliary diversity input values **112***a*/**112***b* input to a trained Generator **102** are allowed to change. In environment **502**, the trained Generator **102** creates game environment data **502***a*-**502***i*, **504** representing a path of platform segment blocks **502***a*-

502*i*, **504** from a starting point platform segment block **502***a* to an overall goal checkered platform segment block **504**. The auxiliary diversity input value was set at $\lambda_{A_i}=1$, which means that the Generator **102** generates an "easily" traversable path for the player character **305** of the Solver **104**. This is illustrated by the closeness of the distances between platform segment blocks representing each sub-goal along the path from the starting point platform segment block **502***a* to the overall goal platform segment block **504**. In environment **512**, the trained Generator **102** creates game environment data **512***a*-**512***g*, **514** representing a path of platform segment blocks **512***a*-**512***g*, **514** from a starting point platform segment block **512***a* to an overall goal checkered platform segment block **514**. The auxiliary diversity input value was set at $\lambda_{A_i}=-1$, which means that the Generator **102** generates an "difficult" traversable path for the player character **305** of the Solver **104**. This is illustrated by the increased distances between platform segment blocks representing each sub-goal along the path from the starting point platform segment block **512***a* to the overall goal platform segment block **514**.

In essence, FIG. **5** illustrates that with a high auxiliary diversity input value, e.g. $\lambda_{A_i}=-1$, the Generator **104** creates a path/track that is easy for the Solver **104** to solve and traverse by controlling the player character **305** to get from the starting point platform segment block **502***a* to the overall goal platform segment block **504**. On the other hand, with a low auxiliary value, e.g. $\lambda_{A_i}=-1$, the Generator **102** is configured to try to make the Solver **104** fail by making a path/track with sub-goals that are difficult for the player character **305** controlled by the Solver to achieve making it more likely the player character **305** falls off of a platform segment block as it traverses the path to the overall goal platform segment block **514**.

FIGS. **6** to **8** illustrate an example Racing game **600** in which the Generator **102** (e.g. first RL agent) is trained to generate and output game environment data **610** for updating the computer game environment **106** of the Racing game **600**, and the Solver **104** (e.g. second RL agent) is trained to interact with the computer game environment **106** of the Racing game **600** and output a set of actions for controlling a player character **605** (e.g. a racing car) in the Racing game **600**. In the Racing game **600**, the Solver **104** or a player controls the player character **605** with the overall goal of traversing as fast as possible to maximize reward along a generated racing track of a plurality of racing track segments **612** iteratively placed by the Generator **102** within the computer game environment **106** of the Racing game **600**. The road or racing track is iteratively created by the Generator **102**, where in each iteration, the Generator **102** creates a new racing track segment for attaching to the unattached end of the racing track segment created in the previous iteration. This iterative process continues until the Generator **102** eventually creates a plurality of racing track segments **612** consecutively joined together that reach an overall goal. The Solver **104** may control the iterative process by requesting a new racing track segment from the Generator **102** prior to completing the current racing track segment **612**. In this manner, the Generator **102** may generate a constant flow game environment data **610** representative of new racing track sections and sub-goals for the Solver **104** to achieve by controlling vehicle **605**. The banking of each racing track segment is dependent on the curvature of the racing track. If the player character **305** (e.g. driver of vehicle) leaves the racing track (or road) it is terminated, otherwise it will continue over the racing track segments until an overall goal is reached (e.g. the road/racing track finishes/terminates) or the episode ends.

In this example, the Generator **104** is configured to generate/create game environment data **610** including racing track segments **612** and actions **614***a*-**614***c* associated with each racing track segment **612** that are representative of sub-goals that lead towards an overall goal (e.g. the end of the racing track, a finish line is reached) within the Racing game **600**. Each of the sub-goals are represented by each of the racing track segments **612** and actions controlling the characteristics of each racing track segment **612** including, without limitation, for example length **614***a* of a racing track segment **612**, turn or curve/bank of the racing track segment **612***b*, and height **612***c* of the racing track segment **612** and/or any other suitable action for controlling the characteristics or features of each racing track segment **312** as the application demands and the like. The Solver **104** is configured to interact with the computer game environment **106** of the Racing game **600** by controlling the player character/vehicle **605** to achieve each of the sub-goals represented by the farthest end of each of the racing track segments **312** and/or overall goal represented by the final sub-goal in the sub-goal sequence using a set of actions based on, without limitation, for example throttle forward/backward actions **606***a* and turn actions **606***b*, and/or any other suitable action for controlling the player character/vehicle **605** as the application demands and the like.

In this example, the Generator **102** includes a Generator network based on a FFNN with at least 2 hidden layers and 512 hidden units per hidden layer, with a hyperparameter γ of 0.990. The RL technique used for training the Generator **102** is based on, without limitation, for example the PPO algorithm and the like with a learning rate of 2e-4. The Generator **104** also receives an auxiliary diversity input value signal **112***a* for use in the Generator reward function as herein described. The Generator **104** receives a first reward **102***b* from the computer game environment **106** of the Racing game **600** along with observation data in the form of the ray cast and the game state array. The observation data provided by the computer game environment **106** of the Racing game **600** to the Generator **102** consists of a ray cast in order to allow the Generator **102** to deploy racing track segments **612** within an already existing computer game environment with obstacles already in place, where the ray cast can be used by the Generator **102** as a collision detector to learn to avoid the obstacles while still creating a traversable racing track with the racing track segments **612**. Further observation data includes the game state vector with data representative of the relative position of the end of current racing track to the overall goal, heading, angle relative to the overall goal, overall goal distance, previous racing track segment position, and auxiliary diversity input value and the like. Further rules may include terminating the episode should the racing track collide with an obstacle in the computer game environment **106** and/or with itself and the like.

In this example, the Solver **104** includes a Solver network based on a FFNN with at least 2 hidden layers and 512 hidden neural units for each hidden layer, with hyperparameter γ of 0.998. The RL technique used for training the Solver **104** is based on, without limitation, for example a PPO algorithm and the like with a learning rate of 3e-4. The Solver **104** receives a second reward **104***b* from the computer game environment **106** of the Racing game **600** along with observation data based on a ray cast and game state vector for providing information on the racing track/road ahead and around the vehicle **605** within the computer game environment **106**. For example, in the Racing game **600** the observation data may include a ray cast around the player character/vehicle **605** of the Solver **104** for use by the Solver **104** to keep track of where the player character/vehicle **605** is in relation to the racing track segments **612** representing sub-goals and/or overall goal and the like. The game state vector may include, without limitation, for example data representative of relative position to the sub-goal/overall goal, heading relative to the sub-goal, angular velocity, velocity, and rotation, and/or any other useful data representative of the vehicle state in relation to the computer game environment **106**.

As an example, the Generator **102** is trained and configured to generate game environment data **610** that includes racing track segments **612** with actions controlling the length of each racing track segment ([20 m, 30 m]), racing track segment curve (e.g. in degrees [−30, 30]), and racing track segment height change (e.g. in metres [−5 m, 5 m]). Each new racing track segment **612** may be requested by the Solver a predetermined distance or dynamically adjusted distance (e.g. in metres 15 m) before the racing track/road or segment ends, which allows the Generator **102** to generate a constant flow of new racing track segments when creating the racing track. The Solver **104** is trained and configured to control the actions of the player character/vehicle **605** by inputting a set of actions **104***a* based on throttle **614***a* and turn **614***b* actions to the computer game environment **106** of the Racing game **600**.

The Generator **102** and Solver **104** are trained based on the RL training processes **120**, **200** and/or **220** as described with reference to FIGS. **1***a* to **2***b* and in relation to the Platform game **300** with reference to FIGS. **3** to **5**. During training, the Solver **104** receives a positive or negative reward from the Solver reward function based on the second reward **104***b* issued from the computer game environment **106** of the Racing game **600**. The Solver **104** may receive a positive reward based on the player character/vehicle **605** moving towards the sub-goal represented by the end of the current racing track segment **312**, moving towards the overall goal (e.g. finish line of the racing track), the time it takes to achieve a sub-goal/overall goal, and/or for completing a racing track segment, completing the track or a sequence of sub-goals/the overall goal. The Solver **104** receives a negative reward for failing to achieve each sub-goal and/or the overall goal, e.g. when the player character/vehicle **605** drives off a racing track segment or times out when attempting to complete the sub-goal associated with a racing track segment or overall goal associated with a plurality of racing track segments. Generally, the reward function for the Solver **104** contains a progressive reward, plus a negative reward for failing. The negative reward for failing is important to have as it stops the Solver **104** from taking too "big a risk" (e.g. driving too fast all the time) when selecting the set of actions **14***a* for controlling the player character/vehicle **605** and consequently forces the Generator **102** to create a computer game environment that is not impossible.

During training, the Generator **102** also receives a negative/positive reward from the Generator reward function, which may be based on the Solver **104** failing and is also dependent on the first reward **102***b* from the computer game environment **106** and the auxiliary diversity input value **112***a*. The Generator reward and computer game environment reward functions include an auxiliary diversity input signal or value **112***a*/**112***b* and is based on those as described with reference to the Platform game **300** of FIGS. **3** to **5**. For example, when the auxiliary diversity input signal is set to $\lambda_{A_i}=-1$ the failing of the Solver **104** is positively rewarding the Generator **102**, where the computer game environment **106** reward function may generate a first reward **102***b* value in the region of, without limitation, for example 10. In another example, when the auxiliary diversity input signal is set to $\lambda_{A_i}=1$ the failing of the Solver **104** is negatively rewarding the Generator **102**, where the computer game environment **106** reward function may generate a first reward **102***b* value in the region of, without limitation, for example −10. Additionally as an option, when $\lambda_{A_i}<0$ a further positive reward may be added for each time step that the player vehicle **605** is above a certain threshold above ground/segment of racing track. As a consequence a $\lambda_{A_i}=-1$ will maximize the air-time of the player vehicle **605** by the Generator **102** creating a heavily undulating racing track, while $\lambda_{A_i}=1$ will give reward for the Generator **102** when the Solver **104** moves towards the overall goal.

FIG. **7** illustrates an example Racing game environment **700** in which a racing track is represented by game environment data of racing track segments **702***a*-**702***l* and **704** that were generated by the trained Generator **102**. In this example, the Generator **102** was trained as described with reference to FIG. **6** and configured to learn how to create a racing track to an overall goal **704** represented by spherical rock formation **704** from an initial start position or racing track segment **702***a*. In this case, the Racing game computer game environment **700** included a plurality of obstacles, for example, obstacles **706***a*-**706***f* that the Generator **102** learned, using ray casting and the game state vector, to iteratively create a racing track that avoids the obstacles **706***a*-**706***f* and create a plurality of racing track segments **702***a*-**702***l* representing sub-goals towards a randomly generated overall goal represented by the spherical rock formation **704**. At the same time the Solver **104** traversed each racing track segment to achieve each corresponding sub-goal represented by it and hence the overall goal **704**.

FIG. **8** illustrates further example Racing computer game environments **802** and **812** when the auxiliary diversity input values **112***a*/**112***b* input to a trained Generator **102** are allowed to change. In environment **802**, the trained Generator **102** creates game environment data **802***a*-**802***g* representing a section of racing track that includes a plurality of racing track segments **802***a*-**802***g*, each racing track segment representing a sub-goal. The auxiliary diversity input value was set at $\lambda_{A_i}=1$, which means that the Generator **102** generates an "easily" traversable or flat section of racing track for the player character/vehicle **605** of the Solver **104**. This is illustrated by the relative flatness of the racing track segments **802***a*-**802***g*. In environment **812**, the trained Generator **102** creates game environment data **812***a*-**812***j* representing a section of racing track that includes racing track segments **812***a*-**812***j*. The auxiliary diversity input value was set at $\lambda_{A_i}=-1$, which means that the Generator **102** generates an "difficult" traversable portion of racing track for the player character/vehicle **605** of the Solver **104**. This is illustrated by the increased undulations of the racing track segments **812***a*-**812***g*. The low auxiliary value (<0) causes the Generator **102** to attempt to make the Solver **104** fail by making a track that increases the likelihood of "throwing" the player character/vehicle **605**, controlled by the Solver **104**, off the racing track.

As described with reference to FIGS. **3** to **5** and **6** to **8**, in both Platform and Racing game environments **300**, **400**, **500**, **600**, **700**, **800**, the auxiliary diversity input value may be used to vary the difficulty of the corresponding computer game environment. In relation to both types of computer game environments, and also other further computer game environments, in order to generate a generalisable Generator **102** and Solver **104**, the auxiliary diversity input values **112***a*/**112***b* that are input to the Generator **102** and the computer game environment **106** may also be iteratively varied during training between ['1, 1] (or [−ATH, ATH], where ATH is the maximum positive auxiliary diversity input value **112***a*/**112***b*) for different episodes/overall goals. For example, the auxiliary diversity input values **112***a*/**112***b*, may be randomly selected from the auxiliary diversity input values of [−1, −1, −0.5, 0.5, 1, 1], which, in the Platform and also Racing game examples was a distribution of auxiliary diversity input values that produced stable results in relation to the resulting trained Generator **102** and trained Solver **104**. As an option, the auxiliary diversity input values **112***a*/**112***b*, λ_{A_i}, may be randomly selected from a set of N>2 auxiliary diversity input values of [−ATH, −y_1, . . . −y_(N−2)/2, y_(N−2)/2, . . . , y_1, ATH], where ATH is a positive real number or integer representing the maximum auxiliary diversity input value, and y_1, . . . , y_(n−2)/2 are positive real numbers or integers in the range [0, ATH]. Alternatively, the auxiliary diversity input values **112***a*/**112***b*, λ_{A_i}, may also be randomly selected from the auxiliary diversity input values as continuous values in the range of [−1, 1] or [−ATH, ATH] and the like, and/or as the application demands.

FIGS. **9** to **11** illustrate the performance results for a trained Fixed agent, a Rule PCG agent and a trained Solver **104** (also referred to as a ARLPCG Solver agent) when operating in unseen computer game environments in relation to, without limitation, for example the Racing and Platform game environments **600** and **300** of FIGS. **6** to **8** and **3** to **5**. To test the generalization ability of the Solver **104** trained using the adversarial RL training system **110** (also referred to as an ARLPCG Solver agent) when trained using a Generator **102** trained using the adversarial RL training system **110** (also referred to as a ARLPCG Generator), several experiments were performed based on training the same RL agent (i.e. same hyper-parameters, observations, actions, rewards, etc.) on differently generated environments. Three approaches were used: 1) Training a Solver agent on a fixed map (referred as Fixed Solver agent) 2) Training a Solver agent on a rule based PCG environment (referred as Rule PCG Solver agent), where, in the rule based PCG environment rules are set for the PCG generator to generate environments based on randomly generated numbers; and 3) ARLPCG system **110** in which a Solver **104** (e.g. ARLPCG Solver agent) is trained using a trained Generator **102** (e.g. ARLPCG Generator) as described with reference to FIGS. **1***a* to **8** with different auxiliary diversity input values input to the ARLPCG Generator in the range of [−1, 1].

FIGS. **9** and **10** illustrate tables **900** and **1000** that show examples of trained Generator **102** output for use by the different types of agents in relation to the Racing game environment as described with reference to FIGS. **6** to **8** and the Platform game environment as described with reference to FIGS. **3** to **5**. These tables **900** and **1000** may be used to quantify if there is some relation between the auxiliary diversity input signal and the output of the trained Generator **102**, in which three different agents were taken and validated with a set of trained Generator **102** generated tracks. For the Solver **104** (also referred in the table as ARLPCG Solver **104**), which was trained by the adversarial RL training system **110**, this can be seen as a function of the training where the Generator **102** learns to adapt to the Solver's **104** behaviour. Tables **900** and **1000** of FIGS. **9** and **10** illustrate how all the three types of trained Solvers can "struggle" more with computer game environments generated by low auxiliary diversity input values (<0 the harder ones) than the computer game environments generated with high auxiliary diversity input values (>0 the easier ones). As can be seen, the trained Generator **102** (or ARLPCG Generator) can be used to create different styles of tracks/goals and computer game environments to a certain degree of difficulty and/or diversity based on varying the auxiliary diversity input value (e.g. varying the auxiliary diversity input value between from 1 to −1, or ATH to −ATH, depending on scaling and the like).

FIG. **9** illustrates a table **900** for comparing the performance of differently trained second RL agents (or Solver agents) on unseen generated computer game environments generated by a trained ARL PCG Generator agent (e.g. first RL agent/Generator **102** of FIG. **1***b*) in relation to the Racing game computer environments **600**-**800** as described with reference to FIGS. **6** to **8**. The differently trained Solver agents are based on the fixed Solver agent, the Rule PCG Solver agent and the ARLPCG Solver agent (e.g. Solver **104**). In this example, these three trained second RL agents, or Solvers, are compared within an unseen Racing computer game environment generated by a trained ARLPCG Generator agent **102** (e.g. a trained first RL agent/Generator **102** of FIG. **1***b*).

Initially, each of the trained Fixed, Rule PCG and ARLPCG second/Solver RL agents are trained using a Fixed, Rule PCG, and ARLPCG generated computer game environment, respectively. Then each trained Fixed, Rule PCG and ARLPCG Solver agent is assessed based on average success ratio and speed on in relation to achieving an overall goal on generated racing tracks within a computer game environment that are generated by a trained ARL PCG Generator agent based on trained first RL agent/Generator **102** described with reference to FIG. **1***b* and/or FIGS. **6** to **8**. The auxiliary diversity input value of the trained ARL PCG Generator agent is varied within the range between [−1, 1] to moderate the difficulty of the output track/computer game environment. The auxiliary diversity input value affects the diversity and/or difficulty of the generated sub-goals and overall goal and resulting Racing computer game environment. The success ratio and average speed reflects the difficulty even for the Solver agents (e.g. Fixed and Rule PCG Solvers) that were not trained using the ARL PCG Generator **102**.

In table **900**, the results for each trained Solver (e.g. Fixed Solver, Rule PCG Solver and ARLPCG Solver) and Auxiliary value are averaged over 2000 trials on 20 tracks, where each track has a simulated scale of being 1 km long within the computer game environment. As illustrated, the trained ARLPCG Solver agent (e.g. Solver **104**) outperforms both the Fixed Solver agent and Rule PCG Solver agents most of the time in terms of either average success rate or overall speed within each of the unseen generated Racing computer game environments. Even though the Fixed Solver agent sometimes has the highest overall speed, it has the lowest success rate which decreases as the difficulty of the unseen generated Racing computer game environment increases (e.g. difficulty increases as the auxiliary diversity input value changes from 1 to −1). The Fixed Solver agent is severely limited for use in unseen computer game environments. Even though the Rule PCG Solver agent has success in completing the overall goals on the unseen generated tracks in the Racing computer game environment, its performance in terms of success error rate and average speed deteriorates compared with the success standard deviation and average speed of the ARL PCG Solver agent **104** achieves as the difficulty or diversity of the unseen racing tracks in the Racing computer game environments increase.

FIG. **10** illustrates a table **1000** for comparing the performance of differently trained second RL agents (or Solver agents) on unseen generated computer game environments generated by a trained ARL PCG Generator agent **102** within in relation to the Platform computer game environment as described with reference to FIGS. **3** to **5**. The differently trained Solver agents are based on fixed Solver agent, Rule PCG Solver agent and ARLPCG Solver agent **104**. In this example, these three trained second RL agents, or Solvers, are compared within the Platform computer game environment generated by a trained ARLPCG Generator agent **102**.

Initially, each of the trained Fixed, Rule PCG and ARLPCG second/Solver RL agents are trained using a Fixed, Rule PCG, and ARLPCG generated computer game environment, respectively. Then each trained Fixed, Rule PCG and ARLPCG Solver agent is assessed in relation to an overall goal within a computer game environment generated by a trained ARL PCG Generator agent **102**. Again, the auxiliary diversity input value of the trained ARL PCG Generator agent **102** is varied within the range between [−1, 1] to moderate the difficulty of the generated platform track/computer game environment. The auxiliary diversity input value affects the diversity and/or difficulty of the generated goals and resulting Platform computer game environment.

In table **1000**, the results for each trained Solver (e.g. Fixed Solver, Rule PCG Solver and ARLPCG Solver) and Auxiliary value are averaged over 50000 trials (50 tracks and 1000 trials). As illustrated, the trained ARLPCG Solver agent **104** outperforms both the Fixed Solver agent and Rule PCG Solver agents within each of the unseen generated Platform computer game environments. The Fixed Solver agent simply cannot complete the overall goals in each unseen generated Platform computer game environment, and so is severely limited for use in unseen computer game environments. Even though the Rule PCG Solver agent is able to complete some of the overall goals in each unseen generated Platform computer game environment, its performance deteriorates compared with the trained ARL PCG Solver agent **104** as the difficulty or diversity of the unseen Platform computer game environment increases.

FIG. **11** illustrates a table **1100** for comparing the performance of differently trained second RL agents (or Solver agents) on unseen generated computer game environments for validation. In this example, two computer game environments were tested based on the Platform game described with reference to FIGS. **3** to **5** and the Racing game as described with reference to FIGS. **6** to **8**. Comparison of performance on a set of previously unseen validation tracks/platforms (1000×20 runs). In relation to the first column in table **1100**, which represents the Platform game example, the Platform game row values refers to success rate, fraction of platform tracks completed by at least one Solver agent, and in brackets average steps taken to reach the overall goal. In relation to the second column in table **1100**, which represents the Racing game example, the Racing game row values refers to success rate and in brackets the average speed. The Fixed track Solver agent is trained on a fixed set of tracks, the Rule PCG Solver agent is trained on rule based PCG generated from a set of rules randomized to create different track every time, Fixed aux. Solver agent is trained from a ARLPCG Generator agent (e.g. trained first RL agent/Generator of FIG. **1***b*) with a constant auxiliary diversity input value, and ARLPCG Solver agent **104** is trained with varying auxiliary diversity input values. As can be seen, the ARLPCG Solver agent **104** outperforms the Fixed track Solver agent, Rule PCG Solver agent and Fixed aux. Solver agent in terms of success rate, fraction of platform tracks completed, and average speed over the racing tracks. This shows that the ARLPCG Solver agent **104** is generalisable and adaptable to unseen computer game environments.

Further modifications to the adversarial RL training systems **100** and **110** and/or Generators **102** and Solvers **104** as described with reference to FIGS. **1***a* to **11** may include using a multi-dimensional auxiliary diversity input functions, which may potentially further increase the diversity of the generated computer game environments generated by a trained Generator **102** and/or the generalisability of the resulting trained Solver agents **104**. Another advantage with the adversarial RL training systems **100** and no is that the resulting trained Generator **102** can generate different computer game environments (controlled via an auxiliary diversity input signal/value) for other use cases, such as real-time map creation. Further modifications may also include, rather than using one Solver **104** per Generator **102**, using a population of Solvers **104** could further improve the diversity of the Generator's **102** output as it would be harder for the Generator **102** to exploit the behaviour of the population of Solvers **104**.

FIG. **12** illustrates a schematic example of a system/apparatus **1200** for performing any of the methods described herein. The system/apparatus **1200** shown is an example of a computing device. It will be appreciated by the skilled person that other types of computing devices/systems may alternatively be used to implement the methods described herein, such as a distributed computing system or cloud computing system and the like.

The apparatus (or system) **1200** comprises one or more processors **1202**. The one or more processors **1202** control operation of other components of the system/apparatus **1200**. The one or more processors **1202** may, for example, comprise a general-purpose processor. The one or more processors **1202** may be a single core device or a multiple core device. The one or more processors **1202** may comprise a Central Processing Unit (CPU) or a graphical processing unit (GPU). Alternatively, the one or more processors **1202** may comprise specialized processing hardware, for instance a RISC processor or programmable hardware with embedded firmware. Multiple processors may be included.

The system/apparatus **1200** comprises a working or volatile memory **1204**. The one or more processors may access the volatile memory **1204** in order to process data and may control the storage of data in memory. The volatile memory **1204** may comprise RAM of any type, for example, Static RAM (SRAM), Dynamic RAM (DRAM), or it may comprise Flash memory, such as an SD-Card.

The system/apparatus **1200** comprises a non-volatile memory **1206**. The non-volatile memory **1206** stores a set of operation instructions **1208** for controlling the operation of the processors **1202** in the form of computer readable instructions. The non-volatile memory **1206** may be a memory of any kind such as a Read Only Memory (ROM), a Flash memory or a magnetic drive memory.

The one or more processors **1202** are configured to execute operating instructions **1208** to cause the system/apparatus to perform any of the methods described herein. The operating instructions **1208** may comprise code (i.e. drivers) relating to the hardware components of the system/apparatus **1200**, as well as code relating to the basic operation of the system/apparatus **1200**. Generally speaking, the one or more processors **1202** execute one or more instructions of the operating instructions **1208**, which are stored permanently or semi-permanently in the non-volatile memory **1206**, using the volatile memory **1204** to store temporarily data generated during execution of said operating instructions **1208**.

For example, the system/apparatus **1200** may be configured for training a first RL agent and a second RL agent coupled to a computer game environment of a video game. The system/apparatus **1200** may include: a generation module for configuring a first RL agent to iteratively generate a sub-goal sequence in relation to an overall goal within the computer game environment, where the first RL agent module generates a new sub-goal for the sub-goal sequence after a second RL agent, interacting with the computer game environment, successfully achieves a current sub-goal in the sub-goal sequence. The system/apparatus **1200** may be configured to also include an interaction module for configuring a second RL agent to iteratively interact with the computer game environment to achieve the current sub-goal, where each iterative interaction includes an attempt by the second RL agent for interacting with the computer game environment to achieve the current sub-goal. The system/apparatus **1200** may also be configured to include a first update module for updating the first RL agent using a first reward issued when the second RL agent successfully achieves the current sub-goal. The system/apparatus **1200** may also be configured to include a second update module for updating the second RL agent using a second reward issued by the computer game environment based on the performance of the second RL agent attempting to achieve said current sub-goal. The system/apparatus **1200** may include an output module for outputting, once the first and second RL agents are determined to be validly trained, a final first RL agent for automatic PCG in the computer game environment, and a final second RL agent for automatically interacting with a PCG computer game environment.

Implementations of the methods described herein may be realized as in digital electronic circuitry, integrated circuitry, specially designed ASICs (application specific integrated circuits), computer hardware, firmware, software, and/or combinations thereof. These may include computer program products (such as software stored on e.g. magnetic discs, optical disks, memory, Programmable Logic Devices) comprising computer readable instructions that, when executed by a computer, such as that described in relation to FIG. **12**, cause the computer to perform one or more of the methods described herein.

Any system feature as described herein may also be provided as a method feature, and vice versa. As used herein, means plus function features may be expressed alternatively in terms of their corresponding structure. In particular, method aspects may be applied to system aspects, and vice versa.

Furthermore, any, some and/or all features in one aspect can be applied to any, some and/or all features in any other aspect, in any appropriate combination. It should also be appreciated that particular combinations of the various features described and defined in any aspects of the invention can be implemented and/or supplied and/or used independently.

Although several embodiments have been shown and described, it would be appreciated by those skilled in the art that changes may be made in these embodiments without departing from the principles of this disclosure, the scope of which is defined in the claims and their equivalents.

It should be understood that the original applicant herein determines which technologies to use and/or productize based on their usefulness and relevance in a constantly evolving field, and what is best for it and its players and users. Accordingly, it may be the case that the systems and methods described herein have not yet been and/or will not later be used and/or productized by the original applicant. It should also be understood that implementation and use, if any, by the original applicant, of the systems and methods described herein are performed in accordance with its privacy policies. These policies are intended to respect and prioritize player privacy, and to meet or exceed government and legal requirements of respective jurisdictions. To the extent that such an implementation or use of these systems and methods enables or requires processing of user personal information, such processing is performed (i) as outlined in the privacy policies; (ii) pursuant to a valid legal mechanism, including but not limited to providing adequate notice or where required, obtaining the consent of the respective user; and (iii) in accordance with the player or user's privacy settings or preferences. It should also be understood that the original applicant intends that the systems and methods described herein, if implemented or used by other entities, be in compliance with privacy policies and practices that are consistent with its objective to respect players and user privacy.

The invention claimed is:

1. A computer-implemented method for training a first reinforcement-learning, RL, agent and a second RL agent coupled to a computer game environment using RL techniques, the method comprising:

iteratively generating, by the first RL agent, a sub-goal sequence in relation to an overall goal within the computer game environment, based on:

generating a new sub-goal for the sub-goal sequence after the second RL agent, interacting with the computer game environment, successfully achieves a current sub-goal in the sub-goal sequence; and

updating the first RL agent using a first reward issued when the second RL agent successfully achieves the current sub-goal;

iteratively interacting, by the second RL agent, with the computer game environment to achieve the current sub-goal based on:

performing one or more actions, by the second RL agent, in the computer game environment to achieve the current sub-goal; and

updating the second RL agent using a second reward issued by the computer game environment based on the performance of the second RL agent attempting to achieve said current sub-goal; and

outputting, once validly trained, a final first RL agent for automatic procedural content generation, PCG, in the computer game environment, and a final second RL agent for automatically interacting with a PCG computer game environment.

2. The computer-implemented method of claim **1**, wherein the state of the second RL agent is frozen whilst the first RL agent performs an iterative generation of said sequence of sub-goals in the computer game environment for the frozen second RL agent to interact with and updating the first RL agent further comprising updating the state of the first RL agent based on a first reward issued when the frozen second RL agent successfully achieves the current sub-goal or times out in multiple attempts at achieving the current sub-goal, wherein said first reward is based on the performance of the frozen second RL agent attempting to achieve the current sub-goal.

3. The computer-implemented method of claim **1**, wherein the state of the first RL agent is frozen whilst the second RL agent performs iterative interactions with the computer game environment in relation to each sub-goal iteratively generated by the frozen first RL agent, wherein updating the second RL agent further comprising updating the state of the second RL agent based on one or more second rewards, each second reward issued by the computer game environment in relation to the performance of each attempt the second RL agent makes when interacting with the computer game environment to achieve the current sub-goal.

4. The computer-implemented method of claim **1**, wherein the frequency of updating the second RL agent based on the second RL agent iteratively interacting with the computer game environment in relation to the current sub-goal is greater than the frequency of updating the first RL agent based on the first RL agent iteratively generating each sub-goal in the sequence of sub-goals in the computer game environment.

5. The computer-implemented method of claim **1**, further comprising applying an auxiliary diversity signal to a reward function of the first RL agent, the reward function of the first RL agent comprising a combination of an external reward and an internal reward, the external reward based on the first reward and the internal reward based on the auxiliary diversity signal and the performance of the first RL agent in generating said sub-goals for achieving the overall goal in the computer game environment.

6. The computer-implemented method of claim **5**, further comprising applying the auxiliary diversity signal to the computer game environment for use in generating the first reward.

7. The computer-implemented method of claim **5**, wherein the auxiliary diversity signal is within a range between a negative threshold value and a positive threshold value.

8. The computer-implemented method of claim **7**, wherein the auxiliary diversity signal is in the range of [−1, 1].

9. The computer-implemented method of claim **1**, wherein the second RL agent is configured to be one of:

a player character within the computer game environment;

a non-player character within the computer game environment; and

an interactive object within the computer game environment.

10. The computer-implemented method of claim **1**, wherein the interactions of the second RL agent is governed by a set of actions enabling at least one of:

the second RL agent solving one or more portions of the computer game environment to achieve the current sub-goal; and

the second RL agent traversing the computer game environment to achieve the current sub-goal.

11. The computer-implemented method of claim **1**, wherein a sub-goal in the computer game environment comprises at least one of:

one or more objects within the computer game environment to be interacted with by the second RL agent in the computer game environment;

a segment of a track or path within the computer game environment to be traversed by the second RL agent in the computer game environment; and

a section of the computer game environment to be solved or traversed by the second RL agent in the computer game environment.

12. The computer-implemented method of claim **1**, further comprising a population of second RL agents, each of the second RL agents being trained for interacting with the computer game environment to achieve the current sub-goal.

13. The computer-implemented method of claim **1**, wherein the input to the second RL agent is game environment data and the output from the second RL agent is player action data for causing a player character in the computer game environment to perform one or more actions to achieve the current sub-goal.

14. The computer-implemented method of claim **1**, wherein the input to the first RL agent is game environment data and the first reward and the output from the first RL agent is game environment data associated with the new sub-goal for updating the computer game environment and causing the second RL agent associated with a player character in the computer game environment to perform one or more further actions to achieve the new sub-goal.

15. The computer-implemented method of claim **1**, wherein the computer game environment is a three-dimensional game environment.

16. The computer-implemented method of claim **1**, wherein the first and second RL agents each comprise a neural network with at least two interconnected layers, each layer comprising a plurality of neural units connected together.

17. The computer-implemented method of claim **16**, wherein the neural network is a feed forward neural network.

18. The computer-implemented method of claim **1**, wherein the RL techniques used for training and updating the first and second RL agents is based on one or more proximal policy optimisation algorithms.

19. A generator RL apparatus for procedural content generation in a computer game environment of a video game, the apparatus comprising one or more processors and a memory, the memory comprising instructions that, when executed by the one or more processors, cause the apparatus to perform operations comprising:

iteratively generating, using a trained generator RL agent trained using a reinforcement learning technique, each sub-goal in a sub-goal sequence within the computer game environment, the sub-goal sequence configured for meeting an overall goal in the computer game environment, wherein a trained solver RL agent or player interacts with the computer game environment in an attempt to achieve a current sub-goal in the sub-goal sequence and, when the trained solver RL agent or player successfully achieves the current sub-goal in the sub-goal sequence, the trained generator RL agent generates a new sub-goal for the sub-goal sequence until the overall goal is achieved by the trained solver RL agent or player; and

updating the computer game environment based on each generated sub-goal for use by the trained solver RL agent or player.

20. A system for training a first reinforcement learning, RL, agent and a second RL agent coupled to a computer game environment of a video game, the system comprising:

a generation module for configuring a first RL agent to iteratively generate a sub-goal sequence in relation to an overall goal within the computer game environment, wherein the first RL agent module generates a new sub-goal for the sub-goal sequence after the second RL agent, interacting with the computer game environment, successfully achieves a current sub-goal in the sub-goal sequence; and a interaction module for configuring the second RL agent to iteratively interact with the computer game environment to achieve the current sub-goal, wherein each iterative interaction comprises an attempt by the second RL agent for interacting with the computer game environment to achieve the current sub-goal;

a first update module for updating the first RL agent using a first reward issued when the second RL agent successfully achieves the current sub-goal;

a second update module for updating the second RL agent using a second reward issued by the computer game environment based on a performance of the second RL agent attempting to achieve said current sub-goal; and

an output module for outputting, once the first and second RL agents are validly trained, a final first RL agent for automatic procedural content generation, PCG, in the computer game environment, and a final second RL agent for automatically interacting with a PCG computer game environment.

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